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Using big data to evaluate the impacts of transportation infrastructure investment
The case of subway systems in Beijing

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Transportation

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Summary

During the past decade, nearly 200 million people in China have migrated from rural to urban areas, making it the largest migration in human history. Rapid urbanization brings improvement in the standard of living and opportunities for economic growth along with huge environmental and societal challenges. The growing urban population and unprecedented increase in vehicle ownership has led to severe traffic congestion and air pollution in virtually all major urban areas in China, a common challenge faced by other emerging economies such as Brazil and India.

To address these challenges, central and local governments in China are undertaking huge investment in transportation infrastructure. China's total investment in transportation infrastructure in 2014 amounted to nearly 4% of its GDP. Subway systems are being developed and expanded in all major cities: China's 12th national five-year plan (2011-2015) outlined 69 new subway lines to be constructed with a total length of 2,100 kilometer and spending of RMB 800 billion (USD 130 billion).

What are the social and economic impacts of these rapid and large-scale investments in transportation infrastructure? To what extent can they address traffic congestion and air pollution problems? Do the benefits from these investments justify their costs? Understanding these questions is important not only for government policies in China but for other emerging economies as well.

In this project, we exploit a variety of data sets and different empirical methods to provide the first thorough assessment of the impacts of the rapid expansion of the subway system in Beijing, China. This study has resulted in three journal articles, two papers published at *the Journal of Environmental Economics and Management*, the other paper published at *American Economic Journal: Economic Policy*. Another paper is in final preparation for submission to an academic journal.

We find that subway expansions in Beijing significantly improved air quality, reduced traffic congestion, and affected travel modes and housing prices. Cost-benefit analysis suggests that total benefits from health and time saving alone would exceed the costs of subway expansion. Most of the cost from subway expansion needs to be justified from traffic congestion relief and other economy-wide impacts, rather than improved air quality. Although different transportation policies can achieve the same level of traffic congestion reduction, they could have very different impacts on the housing market and the spatial pattern of household locations. Both lower-income and higher-income households benefit from subway expansion. However, the welfare increase is significantly larger for higher-income households than lower-income households.

Our results are most externally valid in large, dense cities that have sparse subway systems in place and are considering expansions. China alone has 160 cities that have a population greater than 1 million people. As rapid urbanization in developing countries has become a global trend, our study also provides useful policy recommendations for other developing countries. This is particularly true for India, where PM2.5 concentrations are similar to China and traffic congestion in major cities is getting worse.

Contents

List of figures and tables

Appendix figures and tables

Abbreviations and acronyms

API	Air pollution index
AQI	Air quality index
BHTS	Beijing household travel survey
BPV	Bus passenger volume
BTRC	Beijing transportation research center
CBD	Central business district
CO	Carbon monoxide
CO2	Carbon dioxide
CP	Changping line of Beijing subway system
DID	Difference-in-differences
DX	Daxing line of Beijing subway system
EPA	Environmental protection agency
EV	Expected utility from the possible commuting alternatives
FE	Fixed effect
FS	Fangshan line of Beijing subway system
GDP	Gross domestic product
GPS	Global positioning system
IV	Instrumental variables
MCC	Marginal commuting costs
MECC	Marginal cost of traffic congestion
NDRC	National Development and Reform Commission
NO2	Nitrogen dioxide
O3	Ozone
OLS	Ordinary least squares
PM10	Coarse particulate matter
PM2.5	Fine particulate matter
RMB	The official currency of the People's Republic of China
SO2	Sulfur dioxide
SPV	Subway passenger volume
TAZ	Traffic administration zone
TCI	Traffic congestion index
TVLT	Total value of lost time
VKT	Vehicle kilometers traveled
VOT	Value of time
VSL	Value of a Statistical Life
YZ	Yizhuang line of Beijing subway system
2SLS	Two-Stage least squares

1. Introduction

During the past decade, nearly 200 million people in China have migrated from rural to urban areas, making it the largest migration in human history. Rapid urbanization brings improvement in the standard of living and opportunities for economic growth along with huge environmental and societal challenges. The growing urban population and unprecedented increase in vehicle ownership has led to severe traffic congestion and air pollution in virtually all major urban areas in China, a common challenge faced by other emerging economies such as Brazil and India.

The Chinese automobile industry has grown to be by far the largest in the world, with a total output of around 29 million units including 24.8 million passenger vehicles, in 2017. Private vehicle ownership in China was uncommon before 2000 but the sales of new passenger vehicles in China increased dramatically after the turn of the century, growing from less than one million units in 2001 to nearly 25 million in 2017 and surpassing the U.S. market in 2009. Beijing has led the way in vehicle ownership growth, transitioning from a city on bikes to a city in cars during this period: Beijing’s stock of passenger vehicles increased from about 1.1 million units in 2001 to nearly six million units in 2018. Beijing is now routinely ranked as one of the most congested cities in the world, with the average traffic speed during peak travel times often less than 15 miles per hour.

The Beijing municipal government has been investing heavily in transportation infrastructures, such as buses, roads, and subway lines to combat traffic congestion and air pollution in the city. From 2007 to 2015, the government’s total investment in transportation infrastructure amounted to over 430 billion Yuan (about USD 67 billion). During this period, Beijing rolled out 14 new subway lines with a total length of 440 kilometers. The city’s rapid subway expansion is still ongoing: another 12 subway lines with a total length of nearly 378 kilometers are under construction and scheduled to open before the end of 2020. Similar large-scale expansion of subway systems is taking place in major cities throughout China.

Despite the massive investment in subway infrastructure in Beijing and other major cities in China, rigorous evaluation of the impacts of subway expansion is lacking. What are the social and economic impacts of these rapid and large-scale investments in transportation infrastructure? To what extent can they address traffic congestion and air pollution problems? Do the benefits from these investments justify their costs? Understanding these questions is important not only for government policies in China but for other emerging economies as well.

This project aims to evaluate the impacts of the rapid expansion of the subway system in Beijing, China. Specifically, we explore the following research topics:

1. Effects of subway expansion on traffic congestion
2. Effects of subway expansion on local air quality
3. Effects of subway expansion on residents’ travel modes, housing prices, and welfare
4. Benefit-cost analysis of subway expansion

We employ a number of datasets from various sources. For topic 1, we use administrative data on daily public transportation ridership and road congestion from Beijing Daily Transport Operational Monitoring. For topic 2, we merge the daily air quality measures from 27 air quality monitoring stations and with the map of subway expansion from 2008 to 2017. For topic 3, we combine household mortgage transaction data over 2008-2014 with the 2010 Beijing Household Travel Survey (BHTS) data collected by the Beijing Transportation Research Center.

We have the following main findings. First, road delay time decreases by 15% on average across the city of Beijing after opening of one subway line. Second, an increase in subway density by one standard deviation improves air quality by two percent. Third, subway expansion from 2008 to 2014 increased consumer surplus by 1,390 yuan (in 2010) for a below-median-income household and by 5,410 yuan (in 2010) for an above-median-income household. Fourth, the benefits from health and congestion relief accounts for 1.38-4.36 percent and 58-116.41 percent of the total cost, respectively, during a 20-year period. Recognizing that subway systems could have a life span of at least several decades or over 100 years, our analysis suggests the total benefits from health and time saving alone would exceed the costs of subway expansion.

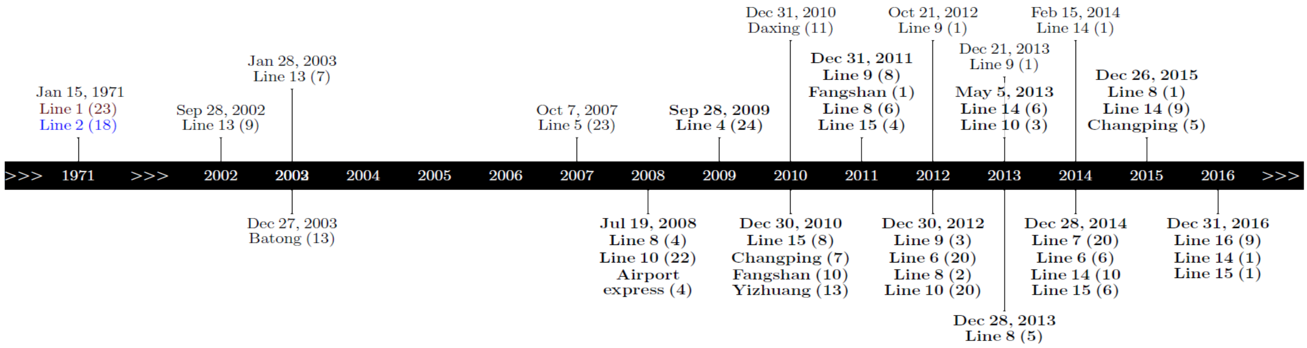
2. Intervention, Theory of Change and Research Hypotheses

2.1 Description

The program we evaluate is the rapid subway expansion in Beijing. Before 2000, Beijing had only two subway lines. After winning the bid for hosting the 2008 Olympic Games in 2001, the Beijing Municipal Government launched the rapid subway expansion program in order to serve the large number of tourists and relieve traffic congestion. After the Olympic Games, the subway expansion accelerated to address the worsening traffic congestion and air pollution as vehicle ownership dramatically increased.

As shown in the subway expansion timeline (Figure 1), two new lines were opened from 2002 to 2006 and new lines were opened every year since 2007. From a global perspective, Beijing's rapid development of mass transit since 2007 is unprecedented. From 2007 to 2014, the total investment in transportation facilities amounted to over 350 billion Yuan (about USD 56 billion). During this period, 14 new subway lines and one airport expressway were constructed with a total length of 440 kilometer. The rapid subway expansion program is still ongoing in Beijing: another 12 subway lines are under construction and scheduled to open before the end of 2020 with a total length of nearly 378 kilometer. Similar large scale and rapid expansion of subway systems are taking place in other major cities throughout China.

Figure 1: Beijing subway expansion timeline

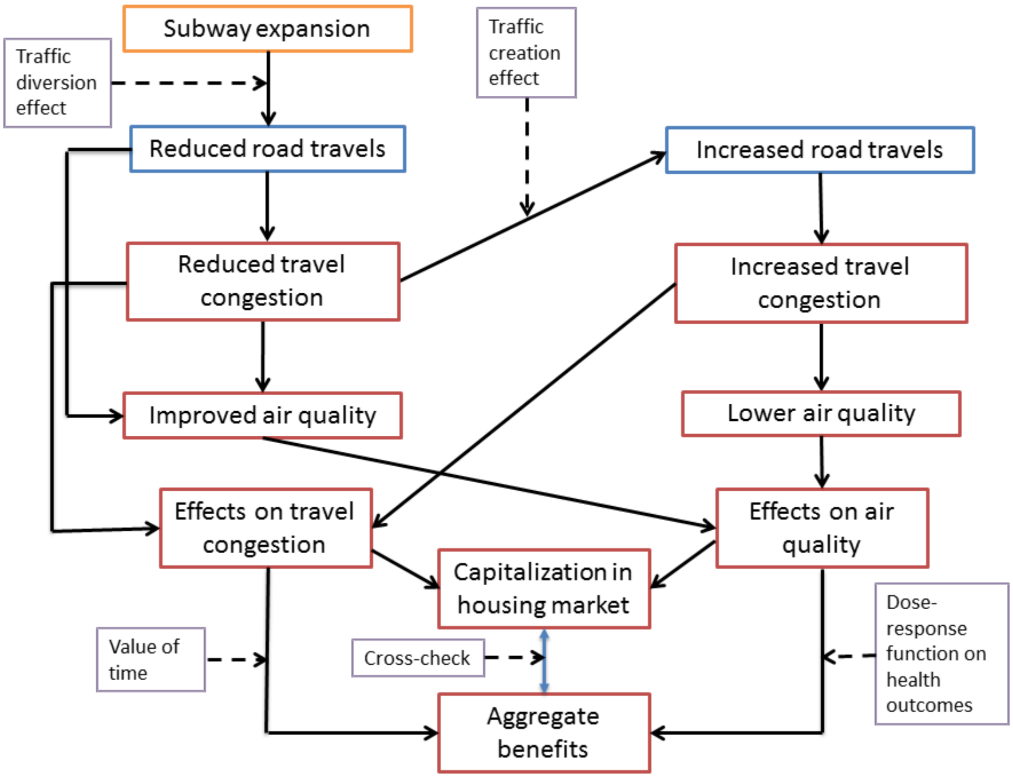


Source: www.bjstats.gov.cn/xwgb/tjgb/ndgb/201402/t20140213_267744.htm.

2.2 Theory of Change

As shown in Figure 2, the expansion of the subway network could impact traffic congestion and air quality through two main channels. First, the improved subway coverage could lead some commuters to switch from traveling using private cars to using subways (Mohring, 1972). This traffic diversion effect or "Mohring Effect" should relieve traffic congestion and reduce air pollution. Second, the improvement in traffic conditions could make driving more attractive and induce additional travel demand using private cars, resulting in a traffic creation effect (Vickrey, 1969) . In the long run, this traffic creation effect could undo the positive impact realized through the first channel. So the net effects of subway expansion on traffic congestion and air quality are unclear and should be investigated empirically. Furthermore, the expansion of subway networks could induce the shift of travel from one area to another. Drivers may shift to roads close to the new subway lines either to utilize the abundant road capacity or to drop passengers at the subway station. Therefore, the expansion of the network could affect traffic condition and air pollution spatially. Our data allow us to examine the heterogeneity effect across space and over time and get a more complete picture of the distributional impacts.

Figure 2: Theory of Change



Although the net effects of subway expansion on traffic congestion and air quality are ambiguous in theory, most existing empirical studies find positive effects of public transit systems on these two outcomes. For examples, Chen and Whalley (2012) used the sharp discontinuity in ridership on opening day of a new rail metro system in Taipei in 1996 to examine the effect of the subway on air quality. They found a significant reduction in carbon monoxide though not in ground level ozone. Using a similar RD approach on a strike in 2003 by Los Angeles transit workers, Anderson (2014) found that the average highway delay increases by 47 percent when transit service ceases.

Based on the theoretical and empirical literature, we hypothesize that

1. Subway expansion reduces traffic congestion;
2. Subway expansion improves air quality;
3. The long run effects of subway expansion on traffic congestion relief and air quality improvement are lower than the effects in the short run;
4. The effects of subway expansion on traffic congestion relief and air quality improvement are larger in the areas closer to the new subway lines than the effects in the areas farther away from the new subway lines.

Subway expansion will also affect property values especially for the neighborhoods close to the new subway stations, because the nearby residents will benefit from easier subway access, relieved traffic congestion, and improved air quality (Baum-Snow and Kahn, 2000; McMillen and McDonald, 2004; Zheng and Kahn, 2013; Li *et al.*, 2016). Lack of property taxation in China allows for housing price to fully capture the capitalization of infrastructure projects into property values. A recent study by two of our principal investigators and their coauthors examined the impacts of Beijing's subway expansion from 2003 to 2008 on housing prices using property-level panel data (Li *et al.*, 2016) . The results suggest capitalization of subway expansion on property values is significant: a 1-kilometer reduction in proximity to a subway station increases property values by 15 percent for properties within 3 kilometers of a subway station, and the effect is 3.4 percent for properties between 3 and 5 kilometers of a subway station (Li *et al.*, 2016).

The rapid subway expansion has been paired with several policies intended to disincentivize car travel: driving restrictions by day, a lottery to be able to purchase a vehicle, and increases in gasoline taxes. We seek in this study to understand how subway expansion and various transportation policies affect household location decisions and housing prices. Since housing and transportation markets feature endogenous prices, we also would like to know how household sorting and commuting decisions affect equilibrium housing price and road congestion levels. While the former has been well studied in the residential sorting literature, most studies of housing location take congestion to be exogenous. We also wish to link these to the effects across Beijing on heterogeneous households.

Relief of traffic congestion due to transit infrastructure reduces travel time, which may generate substantial gains in social welfare measured by the value of saved travel time (Anderson, 2014). Traffic-related air pollution (measured by concentrations of particulate matter, ozone, nitrogen oxides, and carbon monoxide) is associated with increased risk for multiple adverse health effects including asthma and allergic diseases, cardiac effects, respiratory symptoms, reduced lung function growth, adverse reproductive outcomes, premature mortality, and lung cancer (World Health Organization, 2006). Improved air quality will thus contribute to improved health conditions, reduced health-related spending, and lower mortality. The social benefits of subway expansion can thus be imputed based on the value of saved travel time and the dose-response functions that characterize the effects of air pollution exposure on health outcomes from the economic and epidemiological studies, drawing upon the estimated effects of subway expansion on travel congestion and air quality. We will then cross-check the estimated benefits through this social welfare approach with the estimate of capitalization of the proximity to subway in property values described earlier.

3. Evaluation

3.1 Evaluation questions

We have three main evaluation questions:

1. To what extent can subway expansion address the traffic congestion problem?
2. To what extent can subway expansion address the air pollution problem?
3. To what extent can subway expansion (in combination with driving restriction and congestion tax) affect households' travel modes, housing prices, and welfare?

We use secondary datasets from multiple sources to address the research questions. Our research does not involve primary data collection and thus the related ethics issues. Based on available datasets, we use different methods to address the three evaluation questions separately. In next subsections, we describe our data and methods for each of the three questions.

3.2 Data and methods of effects on traffic congestion

3.2.1 Data

Our main outcome variable is traffic congestion. We also look at the effect of subway opening on the subway and bus ridership to shed lights on the mechanism of the effect on traffic congestion. Our empirical analysis leverages daily data on traffic congestion, bus ridership and subway ridership during a 120-window around the each of the opening dates of six subway lines. These administrative data were obtained from Beijing Daily Transport Operation Monitoring, released by the Transport Operation Control Center of Beijing. The data period and subway lines are summarized in Online Appendix Table A1.

To measure congestion, we use TCI, the official standard by which congestion is measured in China. The Beijing Municipal Commission of Transport (BMCT) collects readings on Beijing's road speeds through a large fleet of taxis using satellite navigation and wireless technology at 15-minute intervals. The BMCT assigns weights to different roads and calculates the TCI as a weighted average across Beijing. Online Appendix Table A2 illustrates the relationship between the TCI and the time needed for travel. If all of Beijing's roads flow in an unrestricted manner, the TCI is 0, while if all of Beijing's roads are severely congested, the TCI is 10. For TCI values between 2 and 8, a one-unit increase in TCI corresponds to an approximately 15% increase in travel time. We have three measures of TCI available: total average TCI, morning peak traffic, and evening peak traffic. Our data consist of daily measurements of each of these over the period January 2009 to May 2015.

Online Appendix Table A3 reports simple averages of TCIs and key explanatory variables for the full sample, and before and after the openings of the subway lines. After new subway lines are opened, the traffic congestion index (TCI) decrease by large and statistically significant amounts after subways are opened.

3.2.2 Regression discontinuity approach

We estimate as our primary specification a discontinuity based ordinary least squares model. Our empirical strategy leverages the sharp discontinuities in subway ridership when new lines open:

$$Y_t = \beta_0 + \beta_1 SubwayOpen_t + \beta_2 X_t + \beta_3 SubwayOpen_t X_t + \beta_4 f(X_t) + \beta_5 Z_t + e_t \quad (1)$$

In equation (1), Y_t is traffic congestion, bus ridership, or subway ridership. $SubwayOpen_t$ is a dummy variable indicating whether the new subway lines are open on t. X_t is a running variable representing the time trend: the difference in the number of days between the subway opening and day t. Before the subway opening, X_t is negative; after the opening, X_t is positive. The function $f(X_t)$ is a k-th order polynomial function, used to flexibly control for time-series variation in transportation demand that would have occurred in the absence of the subway openings.

We also include Z_t, a vector of other control variables that may affect transportation. In our regressions involving Z_t, we include four types of additional controls: dummies for the day of week, dummies for extreme weather incidence, dummies for which license plates are excluded from Beijing roads that day, and dummies for which subway opening is being considered. We reason that the first three control variables can impact patterns of transportation. The fourth dummy variable controls for any fixed factor affecting Y_t which differ between openings, such as the larger population and larger economy levels of Beijing in later years.

The variable of interest is β_1, the local average treatment effect of the subway opening on traffic congestion. The size and direction of this effect could vary, depending on how city residents respond to new subway lines. If new subway lines attract passengers from other modes, subway openings will negatively impact bus traffic and ease congestion. However, if new public transportation routes attract new passengers to travel rather than stay home, subway openings could have no effect on measures of travel demand.

The key assumption behind this identification strategy is that the only factor affecting travel demand in the vicinity of subway opening dates is the subway opening. Both observable and unobservable factors affect transportation smoothly in the neighborhood of the subway opening date. Our higher order polynomial function allows us to control for changes from all other factors so long as they are continuous. Other work using a similar methodology in different settings includes Chen and Whalley (2012) and Davis (2008).

We implement this approach using daily observations 60 days before and 60 days after subway openings. We use the period including 60 days before and after the opening of the subway to ensure no overlap between the sample periods of each subway opening. Line 6 opened December 30, 2012, and line 14 opened May 5, 2013.

Our identifying assumption is that, in the absence of subway line openings, demand for transportation would have changed continuously at the time of subway opening. This assumption is reasonable so long as there are no large shifts in the drivers of transportation demand timed with the openings of subway lines. Gradual shifts in transportation demand, which do not threaten our identification, happen on a continual basis: Beijing's economy is growing rapidly, its population is increasing, and the fleet of vehicles in the city continues to enlarge. The flexible polynomial included in our regressions accounts for these continuous changes.

Only discontinuous shifts timed with the six subway openings pose a threat to our identification strategy. A discontinuous shift could occur if subway openings are simultaneous with events that produces changes in travel demand. For example, if Beijing government officials strategically opened Beijing subway lines to coincide with events that decreased transportation demand, our estimates of β_1 would be overstated. However, many details about this setting suggest that precisely timing subway opening dates is not possible.

A second concern in our sample is the extent to which Chinese national holidays can interfere with our results. Several subway line openings occur just before the major holidays of the calendar new year and the lunar new year. We handle this concern by dropping all national holidays in our main specifications. In our robustness checks, we also drop days around holidays to account for the possibility that low transportation demand is observed because some people leave early for vacation or return late from it.

A third concern is the presence of alternative policies that came into effect during our sample period. The most prominent of these policy changes was the January 2011 implementation of the Beijing vehicle license plate lottery system, which sharply reduced the number of new cars on Beijing's roads. A second potentially important policy change was a revision in Beijing's taxi fares in June 2013. We address this concern by dropping the subways openings near these events.

A fourth concern might be that construction activity associated with opening new subways creates congestion. For example, to build street level subway entrances, streets and sidewalks must be closed, possibly increasing congestion; this congestion is alleviated when the new subway line opens. However, this possibility does not fit with the safety regulations of Chinese subways. According to the national standards of subway construction in China, all fully constructed subway lines must be tested for safety for three months before opening to local residents. Since our primary sample period includes congestion levels within only two months of opening, it would not include any street closures or construction activities.

3.3 Data and methods of effects on air quality

3.3.1 Data

Online Appendix Table A4 describes the main variables of our analysis and they are constructed based on three major datasets. The first dataset contains daily air quality readings from all of the 27 monitors in Beijing. Online Appendix Figure A1 shows the spatial distribution of the 27 air quality monitors; 11 of these are operated by the central government, and the rest are operated by the local government. Geographically, eight monitors lie within the 5th ring road, and the rest are outside the 5th ring road. Air pollution in Beijing is measured by two different indices: Air Pollution Index (API), available from January 1, 2008 to December 31, 2012, and Air Quality Index (AQI), available from January 1, 2013 to May 12, 2017. Both indices are measured at the monitoring station level on a daily basis. The API is based on three atmospheric pollutants, sulfur dioxide (SO2), nitrogen dioxide (NO2), and suspended particulates (PM10). In 2013, the Chinese government replaced API with AQI which considers PM2.5 separately from PM10, and includes ozone (O3) and carbon monoxide (CO) as major pollutants. The API or AQI for a given day is calculated based on the level of the dominant pollutant during that day and the dominant pollutant is determined by a scoring system as shown in Online Appendix Table A5.

The second dataset records the opening dates and the locations of subway lines. During the data period from 2008 to 2016, 13 new subway lines and one airport expressway with 252 new subway stations were opened. Online Appendix Figure A1 overlays air quality monitors with subway stations in Beijing as of 2016. Most of the subway stations are located in the central city. Subway stations on the same line could be opened at different dates. For example, some subway stations on Line 8 were opened on the same day as Line 9. Our analysis is thus based on ten major opening dates during the sample period (Figure 1).

The third dataset contains daily weather variables: average temperature, average relative humidity, precipitation, and binary variables indicating rain, snow, storm, and fog. It also includes hourly wind direction (measured in degrees from 0◦ to 359◦) and speed. Wind plays an important role in air pollution because it affects the movements of the fine particulates. Since our unit of observation is daily, we need to convert hourly wind speed and direction to the daily level. We calculate the daily wind direction and speed based on the vector summation of hourly wind direction and speed. We then categorize the daily wind directions into 16 groups. Online Appendix Table A6 presents summary statistics for the main daily weather variables and the daily wind directions.

Online Appendix Table A7 presents the sample averages of ln (Air Pollution) 60 days before and after the opening of each new subway line. The top panel shows the simple averages, while the bottom panel presents the average residuals after controlling for weather conditions and a rich set of time and location fixed effects (including monitor, year, season, day of week, and holiday fixed effects, the same set of controls to be used in the regression analysis). The treatment group is defined as the monitoring stations within 2km of a new subway line, while the control group is defined as the monitoring stations more than 20km away from the new subway line. The top panel shows a 4 percent increase in air pollution level on average after the opening of a subway line. This counterintuitive result could be driven by seasonality: nine out of the 14 new lines were opened in December and air quality tends to be worse in January and February than in November and December due to winter heating. The bottom panel shows that after partialling out time and location fixed effects and weather conditions, the opening of a new subway line is associated with a 4.6 percent reduction in air pollution level on average

Online Appendix Figure A2 depicts average residuals of ln(Air Pollution) from 60 days before to 60 days after the opening of each new subway line for the treatment group and the control group, after partialling out weather conditions and a rich set of time and location fixed effects. The treatment group appears to have a higher air pollution level than the control group (relative to their baseline levels) one month before the opening of the new lines but have a lower level of air pollution about 20 days after the opening. The difference between the two groups seems to increase over time after the opening with the treatment group exhibiting a lower level of air pollution.

3.3.2 Subway network density and instrumental variable approach

The main empirical framework employs subway network density as the key explanatory variable and uses the instrumental variable (IV) approach to address endogenous subway locations. The key explanatory variable in this specification is an inverse distance- weighted subway density:

$$Density_{it} = \sum_{j \in \mathcal{N}_t} \frac{1}{Distance_{ij}^2},$$

where *i*, *j*, and *t* index air pollution monitoring stations, subway stations, and days, respectively. N_t is the set of existing subway stations at time *t*. The subway network density for monitoring station *i* at time *t* is the weighted number of subway stations at time *t*, in which the weight is the inverse of squared distance from the monitor to a corresponding subway station in operation at time *t*. Following the density measure commonly adopted in the urban literature (Ewing and Cervero, 2010), this measure can be considered as the number of subway stations per unit area centered around a given monitoring station. The density measure increases with the number of subway lines. However, a new subway line will change the density measure differently across monitoring stations. The density will increase more for the monitoring stations closer to the subway line.

This subway density measure, however, does not account for the heterogeneity across subway stations or subway lines in their contribution to the whole subway system. For example, major transfer stations that connect multiple subway lines or subway lines in the center of the system play more important roles in the connectivity of the system. To capture this heterogeneity, we generate an alternative density measure which takes into account the ridership of each subway line for robustness checks.[1] The following equation shows the ridership-weighted subway density measure ($\widetilde{Density}_{it}$):

$$\widetilde{Density}_{it} = \sum_{j \in \mathcal{N}_t} \frac{Weight_{jl}}{Distance_{ij}^2},$$

where $Weight_j$ denotes the weight of subway station *j* on subway line, which equals the ridership share of line among all subway lines in operation at time *t*.

Online Appendix Table A8 reports the number of new stations at each opening and the average standardized density in the vicinity of air quality monitors at each opening.

We estimate the following equation:

$$\begin{aligned} \ln(Air\ Pollution_{it}) = \beta_1 \left(\frac{Density_{it}}{\sigma}\right) + Monitor_i + \ Trend_{it} \\ +Weather_t\beta_2 + Monitor_i \times Driving_t \\ +Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it} \qquad (2) \end{aligned}$$

The outcome variable, $\ln(Air\ Pollution_{it})$, is the logarithm of daily Air Pollution Index (API) during 2008-2012 and Air Quality Index (AQI) from 2013 onward. $i = 1, \ldots, 27$ is the index for monitoring stations and $t \in$ [Jan 1, 2008, Dec 31, 2017] is the index for day. The key explanatory variable is the standardized subway network density to facilitate interpretation, where $Density_{it}$ is defined above and σ is the standard deviation of the density. $Weather_t$ is a vector of weather variables including average temperature (*C*), relative humidity (%), wind speed (m/s), precipitation (mm), dummies for rain, snow, storm, and fog, and 16 wind direction dummies.

We include monitor fixed effects ($Monitor_i$) to control for unobserved location attributes that affect air quality. We also control for a set of temporal fixed effects including year fixed effects ($Year_t$), season fixed effects ($Season_t$), day of week fixed effects (DoW_t) and holiday fixed effects ($Holiday_t$). To control for other confounding factors that may vary across time but are not adequately controlled by the time fixed effects, we include a

[1] The ridership information at the subway station level would be ideal to be used as a weight. Unfortunately, we could not find such data set at this point. To proxy the ridership at the station level, we use ridership data at the subway line level, treating that each station in a certain subway line has the same ridership.

monitor-specific time trend, $T\ rend_{it}$, to allow the unobserved time trend to vary across monitors.[2] We also interact monitor fixed effects with driving restriction policy ($Driving_t$) to allow the effects of driving restrictions to vary by locations. Beijing's driving restriction policy bans some vehicles from driving on a given workday depending on the last digit of the license plate number. This policy follows a pre-set rotation schedule in terms of which pair of numbers (1 and 6, 2 and 7, 3 and 8, 4 and 9, or 5 and 0) is restricted on a given day, and it is not adjusted based on traffic conditions. Because the last digits of license plates are not evenly distributed and this policy thus changes the traffic conditions on the road (Yang, Purevjav and Li, 2019), we construct $Driving_t$ as a vector of five dummies indicating the five pairs of the last digits of license plates. ε_{it} is the random error term.

The key identification challenge is the potential endogeneity of the density variable resulting from non-random placement of subway stations. City planners may place the subway lines and stations in anticipation of the future growth (e.g., population or commercial activities) of different parts of the city, which could have implications for the traffic congestion level. If the subway lines are more likely to be placed in areas with higher anticipated growth of economic activities (hence congestion), the framework using the network density as the key explanatory variable may underestimate the impact of subway expansion on air quality improvement.

To address the concern of non-random placement of subway stations, we use the historically planned subway network to construct an instrument for the density measure, following Baum-Snow (2007), which uses historical highway plans in the U.S. to instrument for observed highway routes.[3] We obtain historical subway plans in 1957, 1983, 1999 and 2003. We use the 2003 plan to construct the instrument because it has the most lines and because many of the lines appear in earlier plans. The 1957 plan is the first known plan and provides the basis for the subsequent plans while the 1983 plan defines the "Horizontal+Vertical+Ring" framework of the Beijing subway system, which continues to be used. Because we do not observe the planned opening dates from the historical plans, we assign the actual opening dates to the planned lines. In order to introduce another layer of randomness, we also implement random opening dates within a window of the observed opening date as a robustness check.[4]

The exogeneity assumption of the IV hinges on the fact that the original subway plan were designed to facilitate national defense, with little or no regard for future travel demand or air quality. Many of the lines were planned several decades before the construction, long before air pollution and traffic congestion became a concern. During the first planning period of the subway system about 60 years ago, the population in Beijing was less than 3 million, with only 5,000 vehicles. Building a subway system

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[2] *Trendit* is a vector of monitor-specific linear time trends (the interaction of the dummy for monitor *i* and the linear time trend *t*).

[3] We construct the IV following the same density measure as described earlier while just replacing actual subway stations with the planned ones?

[4] Following Faber (2014), we construct an alternative IV in the earlier version where we use the minimum spanning tree (MST) method to construct hypothetical subway lines with the origin and destination given by the historical subway plans. We straighten up all the historical subway lines and reallocate the observed subway stations to the nearest location on the hypothetical lines. We find similar results using the two different sets of IV.

requires huge investments and advanced technologies. The then-premier, Zhou Enlai, said, “Beijing is building the subway purely for defense reasons. If it was for transport, purchasing 200 buses would solve the problem.”[5]

Beijing’s vehicle stock was only 1.5 million in 2003, compared to nearly 6 million by 2018. The rapid increase in vehicle ownership after 2003 was unlikely to be predicted by policy makers and the historical plan is thus unlikely to be correlated with the spatial pattern of traffic congestion and air pollution within the city. The IV is correlated with the density measure because the constructed subway lines largely follow the historical plans, which contain a similar number of transferring stations and level of connectivity as the current subway system.

The empirical approach based on subway network density relies on the spatial and temporal variation of the network expansion. The subway density measure is not a city-wide measure but is local in nature. A new subway line would increase the density more for nearby monitoring stations than for those farther away from the line. The underlying assumption is that the impact of subway expansion on air quality is not uniform across the city but diminishes over distance. With this assumption, this approach allows for system-wide impact or the spatial spillover effect of subway expansion on air quality.

3.3.3 Difference-in-differences (DID) specification

As an alternative specification, we use the DID method which assumes the impact of subway expansion to be confined locally. This assumption allows us to define treatment and control groups. While this assumption may appear to be ad hoc, the advantage of the DID approach is that it can be easily adapted to examine the potential heterogeneity in impacts (e.g., the dynamic impact over time).

Our DID strategy compares the air quality 60 days before and 60 days after each of the 10 opening dates of subway stations between the treatment and the control group. Since the subway lines are designed to serve different areas of Beijing, the set of treated and control monitors vary across different opening dates. We choose the time windows to be 60 days before and after the opening dates to avoid the overlap between the pre-opening and post-opening periods of two consecutive lines. In DID regressions, we restrict our sample to the observations that fall in the 120-day windows around the opening dates.

We define the treatment group as the monitoring stations within 2km of a subway station and the control group the monitoring stations farther than 20km of a subway station. We treat the area in between as the buffer zone and drop the monitors in the buffer zone in the DID analysis to address the concern of misclassifying treatment status.

The choice of the treatment group is based on the radius of the impact on commuters’ mode of travel to subway stations. The typical length of time that commuters take to

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[5] A quote from the article “The birth of the Beijing subway: Premier Zhou said that the preparation of the subway is to prepare for the battle” well explains the situation that China faced back in the 1950s, “In June 1950, the new China, which was just half a year after the founding of the People’s Republic of China, was forced to become involved in the Korean War. At the same time, the US Seventh Fleet entered the Taiwan Strait. ... In such an international situation, war preparedness should be the first factor to be considered in Beijing’s urban planning.” http://discovery.cctv.com/20070926/100879.shtml.

travel to subway stations is between 5 and 15 minutes. Walking and biking are the two most common commuting modes to subway stations in Beijing. The typical walking distance is about 1km (or 12 minutes based on a walking speed of 5km/hour) while the typical biking distance is about 3km. We choose the average of the two as the radius of impact to define the treatment group.[6]

As the subway system is a network, the impact of the opening of a new subway station on air quality could go beyond 2km. The DID provides estimates of *local* effects within 2km of subway stations, which is different from the estimates of city-wide effects in the density specification discussed earlier. The impact is likely to be larger in the areas closer to subway stations due to the stronger impact on travel mode choices. Therefore, we expect the estimates from the DID to be larger than the estimated impacts from the IV method using the density measure, which is confirmed by our empirical findings (to be discussed later).[7]

Following a general framework by Bertrand, Duflo and Mullainathan (2004) and Hansen (2007) with multiple groups and time periods, the basic DID framework is specified as

$$\begin{aligned} ln(Air\ Pollution_{it}) = \theta Treated_{it} \times 1(Post_t) + Monitor_i + Trend_{it} \\ + Weather_t \beta + Monitor_i \times Driving_t \\ + Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it}, \qquad (3) \end{aligned}$$

where $Treated_{it}$ is a treatment indicator that takes the value of 1 if monitor *i* is within 2km of any subway stations that were opened on date τ ($\tau - 60 \leq t \leq \tau + 60$). $\mathbf{1}(Post_t)$ is a dummy variable indicating whether an observation is within 60 days *after* opening of these new subway stations, that is, $\tau \leq t \leq \tau + 60$. The parameter of interest is θ which captures the impact of the subway opening on air pollution for areas in the vicinity of the new subway stations within 60 days after the opening. Other control variables are defined as in Equation (2).

The key assumption of the DID is that, in the absence of a new subway opening, air quality in the treatment and control groups follow parallel trends. Most monitoring stations in the control group are in the suburban districts of the city as shown in Online Appendix Figure A1. One may be concerned that those monitors in the control group may be too far away from the city center and thus would have different trends from those in the treatment group. We take two strategies to address this concern. Our first strategy takes advantage of the staggered rollout design of the subway lines. We use the monitors that are located 20km farther from the new subway stations but within 2km distance of subway stations either opened in the past or to be opened in the future as the control group. Because both the treatment and control groups contain only monitoring stations that are close to subway stations, the two groups likely share similar (observed and unobserved) characteristics. The underlying assumption of this method is the randomness of the opening date.

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[6] The walking and biking distances are approximated based on the Guideline of Designing and Planning for Areas along Urban Rail from Ministry of Housing and Urban-Rural Development of the People's Republic of China, and Yang *et al.,* (2018b). We also conduct a spatial lag analysis to determine the 2km cut-off for the treated and 20km cut-off for the control groups. The results are available upon request.

[7] To the extent that the opening of a subway station could impact the traffic flow of the whole city including areas 20km away, the DID approach confounds control with treatment and could underestimate the true impact. Indeed, when we define the control group as the monitoring stations 15km away from a subway station and shrink the buffer zone accordingly, we find a smaller impact, consistent with the intuition above. We choose 20km to reduce the potential bias.

Second, we use event study analysis to show the parallel trends hold for pre-opening periods in general. We divide the 120-day time window around opening dates into twelve 10-day intervals (six pre-opening periods $n = -5, -4, ..., 0$, and six post-opening periods $n = 1, 2, ..., 6$) and run the following regression:

$$ln(Air\ Pollutionit) = \sum_{n \neq 0} \delta_n P_t(n) \times Treatedit + Monitori + Trendit$$
$$+Weathert\beta + Monitori \times Drivingt$$
$$+ Yeart + Seasont + DoWt + Holidayt + \varepsilon_{it}, \qquad (4)$$

where $P_t(n) = \mathbf{1}[\tau + 10 \cdot (n - 1) \leq t \leq \tau + 10 \cdot n]$, indicating interval n. The base interval is the 10-day intervals before the opening dates (i.e., $n = 0$).

Online Appendix Table A9 presents the coefficient estimates of δ_n. The results support the parallel trends assumption in general: compared with the base interval (10-day window before opening dates), the subsequent changes in air quality between the treatment and control groups are not significantly different for four out of the five pre-opening intervals in the specification exploiting staggered rollout design (Column 4). In the specification that does not exploit the staggered rollout design (Column 3), three out of the five pre-opening intervals show parallel trends, with the base interval and the parallel trends assumption only being marginally rejected in one of the remaining two intervals. In contrast, we find statistically significant effects of air pollution reduction in four out of six post-opening intervals for the same two specifications (Columns 3 and 4).

One additional identification concern may arise from air pollution induced by subway construction, which differs between the treatment and the control group. The construction of a subway station involves both underground and ground work, which may generate construction dust and worsen the air quality. If the construction leads to higher pollution levels close to new subway stations before opening dates, the DID framework could mistake the pollution reduction from the mere completion of the construction itself as the impact of the subway expansion and hence overestimate the true impact. However, this concern is mitigated because under the national standard of subway construction in China, every subway line is subject to an intensive trial run over a three-month period during which the subway train is tested after the ground work has been finished completely.[8] Since our DID analysis focuses on the 120-day window around opening dates during which the subway construction is already completed, we do not expect construction dust to confound our results.

We estimate two alternative specifications to relax the assumption of uniform effects of subway opening across opening dates and stations. First, we allow the impact to vary by number of days after the subway opening, as specified in Equation (5).

$$ln(Air\ Pollutionit) = \psi 1 Treatedit \times 1(Postt) + \psi 2 Treatedit \times 1(Postt) \times Dayst$$
$$+ \psi 3 Treatedit \times 1(Postt) \times Days2t + Monitori + Trendit + Weathert\beta + Monitori$$
$$\times Drivingt + Yeart + Seasont + DoWt + Holidayt + \varepsilon it \qquad (5)$$

here $Days_t$ is the number of days after the opening of the subway station. This specification allows the effect to occur gradually since it may take time for commuters to adjust their travel modes.

[8] The first phase of the trail run process has no passengers on board and during the second phase of the process, typically the last 20 days of the process, the subway with passengers (not the public) will be tested following the scheduled time and route.

In the second specification, we examine the heterogeneity of treatment effects by allowing the impact to differ based on the number of new subway stations within the vicinity of the treated monitors as in Equation (6).

$$ln(Air\ Pollution_{it}) = \eta N_{it} \times Treated_{it} \times 1(Post_t) + Monitor_i + Trend_{it}$$
$$+Weather_t\beta + Monitor_i \times Driving_t$$
$$+ Year_t + Season_t + DoW_t + Holiday_t + \varepsilon_{it} \qquad (6)$$

where N_{it} is the number of subway stations opened at date τ ($\tau - 60 \leq t \leq \tau + 60$) within the 2km distance of the monitor *i*. This specification captures the notion that when more subway stations are located nearby, commuters are more likely to use the subway to reach their destinations and hence to reduce driving and air pollution more in the vicinity areas.

3.4 Data and methods of effects on travel mode, housing prices, and welfare

3.4.1 Data

To examine how Beijing households respond to the transportation policies including subway expansion, driving restriction, and congestion tax, we construct the detailed housing and work commute dataset to study equilibrium sorting behavior. This dataset combines household-level mortgage transaction data including complex, unit, borrower and co-signer characteristics for 13,865 households purchasing homes in Beijing over 2008-2014. Critically, this mortgage dataset also includes home and work street addresses, which allows us to identify the implied commute to work for a particular home location and compare it to that for alternative homes in the household's choice set. In order to understand the relative benefit of any particular commute to work, we then match these potential home and work location pairs to choices made by households in a separate travel survey conducted in 2010 in Beijing. We begin first by describing this data.

We utilize the Beijing Household Travel Survey (BHTS) for observations based on data collected in September and October 2010 by the Beijing Transportation Research Center (BTRC), an agency of the Beijing municipal government. The BTRC has conducted annual household travel surveys for many years, and the Beijing municipal government uses these surveys to understand Beijing residents' travel behavior and to inform transportation policies. Academic researchers have also used the survey data to analyze transportation in Beijing (Wang et al., 2014).

The BHTS comes from a multistage sampling of households in Beijing in 2010. BTRC randomly selects a subset of Traffic Analysis Zones (TAZs) from the 1,911 in the entire city. TAZs are geocoded areas about 1.5 square kilometers, on average, although their size also depends on the density of trip origins and destinations, which smaller TAZs located closer to the center of Beijing reflecting the greater density of employment, housing and commercial retail there. The survey covered 46,900 households, 116,142 individuals, and 253,481 trips. Panel (a) of Online Appendix Figure A3 shows the set of TAZs sampled for the 2010 BHTS with the core of urban Beijing and outside of it. We only consider households living within the 6th ring road, which corresponds to most of urban Beijing.

Each record in the travel survey reflects a single home-to-work or work-to-home trip for a household using a certain commuting mode or modes and records the TAZ of the origin and destination locations. For the purposes of the estimation detailed earlier, we need to construct counterfactual trips to understand the characteristics of the trip had it been taken using an alternative mode. We use the centroid of the TAZ from the origin and destination of each location and then calculate travel times and distances by submitting the corresponding latitude and longitude to Google Maps' Application Program Interface (API) server for processing.

In principle, there are a large number of possible modes or mode combinations that any commuter could travel on between home and work. To focus on modes which we observe with regularity in the data and to make the choice modeling tractable, we keep only travel survey observations for trips where there is a single mode and it is either Driving, Subway, Bus, Walking, or Biking, which is the bulk of all trips in the data. Calculating time and distance for the subway using Google Maps is complicated by the fact that the API is unable to simulate the transit network as far back in the past as 2010. Since the subway network has changed dramatically since then, as discussed earlier, and understanding counterfactual travel times and housing choices in the absence of these expansions will be the focus of simulations, we use an alternative method to calculate subway trip information. First, we assume that households walk to and from the nearest subway station on either end of the subway trip. We then use Geographical Information System (GIS) cartographic data of the subway network extent for the day the trip was taken to estimate the travel distance and time between the stations nearest to origin and destination.

To estimate the model described below, we construct two attributes of each possible trip, pecuniary and time costs. The former (0.75 RMB/km) is constructed for driving based on the cost of gasoline and average fuel economy in Beijing in 2010. Based on the data about fares in the travel survey, the average cost of a subway trip is 2RMB. For bus travel, there is a 2RMB base fare, which we then adjust based on expected transfers.[9] Walking and biking are assumed to have zero marginal cost. Time costs are based upon the travel time for the trip reported by the Google Maps API.

Panel A of Online Appendix Table A10 reports summary statistics from the travel survey data. We can see that average income is 64,490 RMB, which is almost twice per capita income reported by the China Statistical Yearbook for 2010 of 33,360 RMB, which reflects the fact that these households are more predominantly in central Beijing, are employed and have a fixed dwelling. It is also noteworthy that less than a third of households sampled own a car. This is roughly what the overall pattern of car ownership in the city is from the statistics from the China Statistical Yearbook. Turning to Online Appendix Figure A4, we can see the distribution of mode choice and travel times in Beijing from the survey. It is noteworthy that while roughly a third of households own cars, driving only accounts for 15% among all trips, reflecting that some of the policies discussed above may have disincentivized driving and the fact that the car may be used by a different member of the household. It is also noteworthy how low the share of subway ridership is (5.3%) and how relatively long the trips taken on it are. These long trips may reflect the fact that many of these individuals do not have a car and are commuting longer distances for which biking, walking or bus are even more time consuming.

Our second dataset consists of transaction-level data for issued mortgage applicants from the largest mortgage provider in Beijing. The underlying dataset includes 72,144

[9] Transfer costs are 0.2 yuan for students, 0 for elderly people, 0.4 yuan for people with public transportation cards, and 1 yuan for people without public transportation cards.

mortgage transactions from 1995-2014. The coverage varies from year to year, increasing over time. To capture housing demand around the time of Beijing's subway boom and for years where we have sufficient mass of observations, we restrict the sample to 13,865 transactions over 2008-2014. The mortgage data includes information about household attributes including income, age, marital status, residency status (hukou), and critically for our analysis, the address of the household's work location. We also no for each purchased property the transaction price, date the mortgage was signed and the street address. We contracted with a Beijing-based company to geocode these home and work addresses to a specific latitude and longitude.

As discussed below, we will need to use predict commuting times and distances for households in the mortgage dataset to estimate our sorting model. For computational tractability, we construct the choice set of a household in our data based on a random sample of 20 homes from the set of all potential houses a household could choose within a two-year window around the date we observe their actual home purchase. For each household, we construct commuting distances and times for each housing choice (potential or actual) to the borrower's workplace. We do this in the Google Maps API based upon regions of Beijing corresponding to the intersection of district boundaries with ring roads. There are 25 of these regions as shown in panel (b) of Online Appendix Figure A3, although those outside the 6th ring road are not used. Because our data report the work location of the principal borrower of the mortgage, when we refer to the household's work location, it is this one, though in principle there may be multiple work locations depending upon the labor supply decisions of any particular household.

To identify mean utility parameters in the estimation described below, it is necessary to have sufficient variation in the share of each alternative. Because a single house is only chosen by a single household in our data, we need to define housing choices in a more aggregate form. Following Tra (2010) and Bayer, Ferreira and McMillan (2007), we collapse the mortgage observations into housing types with attributes based on mean values of the houses within. A single housing type corresponds to a representative house in a given jiedao, roughly a neighborhood, within a two-year window. Online Appendix Table A11 reports summary statistics from the mortgage data. We can see that household income is even higher reflecting the fact that these households are wealthy enough to purchase a house and qualify for a mortgage. The average distance to work is 10.5km, which is roughly the distance from the center of Beijing to the 3rd ring road, although distances can be as big as 53m, which is a little less than the distance to the 6th ring road. Distances to subways are about half as far away on average, but can also be quite far for households living in outlying areas.

3.4.2 Empirical framework of a structural estimation

In this section we lay out the components of a two-stage model to estimate the demand for housing based, in part, on the commuting options available to a given household in that housing location. We assume that households choose a house based on their preference for housing attributes, commuting alternatives, and neighborhood amenities. The aggregation of individual choices affects the supply of amenities such as pollution, congestion and public education, and controlling for the endogenous formation of these amenities has proven important in estimating household sorting models (Bayer and Timmins, 2005). The equilibrium sorting model presented here characterizes these processes and recovers the underlying housing consumption preferences from choice data.

The choice of a housing location based upon commuting patterns is one part of a joint decision of work and home location choice. The choice of these locations may be simultaneous or sequential, but it is likely that the levels of endogenous amenities will affect both choices following Rosen (1979) and Roback (1982). Because for many households the choice of work location is likely to be the outcome of a longer-term process of labor supply and migration decisions, we take it as given for the purpose of our model. Therefore we define our model as a housing location model within which is nested the expected value of all potential commuting options at that location. Because we do not observe commuting decisions for households in the mortgage data, our approach is to estimate preferences for mode choice from the travel survey. Then using these estimates, we construct a location- and household-specific measure of the value of commuting options for housing locations in the mortgage data. We lay out the framework for this two-stage model below.

Housing demand model. The indirect utility for a household i choosing to live in housing type j can be written as:

$$\max_{\{j\}} V^i_{j\in J} = \alpha^i \log(p_j) + X_j\beta^i + \gamma^i EV^i_j + \xi_j + \varepsilon^i_j, \qquad (7)$$

where y_i is household income, p_j is the price of housing type j, X_j is a vector of housing type attributes, EV_i is expected utility from the possible commuting alternatives, ξ_j is a vector of unobserved attributes, and ε_i is Type I Extreme Value error. The marginal utility for each housing attribute can be separated into an individual-specific component and a mean component so that: $\alpha_i = \bar{\alpha} + z_i\alpha$ and $\beta^i_j = \bar{\beta}_k + z_i\beta_k$, where z_i are household demographics. Reflecting the fact that the marginal disutility of housing prices is dependent upon income, we estimate our model with specifications that replace $\log(p_j)$ with $\log(\frac{p_j}{y_i})$. In addition, as discussed below, because household i's commuting decision depends on the location of housing type j, the term EV_i will vary based upon the work and home location of every household-housing type pair.

Mode choice model. For commuting, which represents derived demand from household labor supply decisions (as well as other time allocation decisions such as leisure, house work and travel), the most salient characteristics of utility-maximizing households in weighing commuting options is their time and financial costs.[10] To reflect these costs, we consider the choice of mode m (among those available for commuter c in location j: Mc) by commuter c living at housing location j as:

$$\max_{\{m\in M^c_j\}} v^c_{jm} = \theta_{jm} + \gamma_1 time^c_{jm} + \frac{\gamma_2 cost^c_{jm}}{y^c} + \eta_m z_c + \varepsilon^c_{jm}$$

where θ_{jm} is a mode-specific fixed effect, and $\theta_{j,walk}$ normalized to zero. This fixed efect incorporates mode-specific amenities, disamenities, scheduling or inconvenience costs that do not scale with the time or distance traveled. $time^c_{jm}$ is the time of commuting from housing type j to work using mode m, $cost^c_{jm}$ is the monetary cost for that trip, y^c is the income of commuter c, and ε^c_{jm} is Type I Extreme Value error. A convenient property of the functional

[10] Preferences for particular attributes of commuting modes may matter as well such as the enjoyment of driving a car, perceived “greenness” of using public transportation, or health benefits of biking or walking. We include mode- specific fixed effects in the model below to account for these.

form assumed here is that it allows the financial burden to scale with income and it provides a straightforward means to calculate the value of time (VOT) as: $\frac{\gamma_1}{\gamma_2} \cdot y^c$. Estimating this model on the travel survey data produces parameter set $\hat{\Theta} = \left\{\{\hat{\theta}_j\}_{j=1}^{J}, \widehat{\gamma_1}, \widehat{\gamma_1}\right\}$, where $\hat{\theta}_j = \{\theta_{jm}\}_{m=1}^{M_j}$. We then use these estimates to construct the logsum form of expected utility for all commuting alternatives using time, cost and income data for households i from the mortgage data based on the home and work locations for a given home choice:

$$EV_j^i = \log\left(\sum_{m\in M_j^i} exp\left[\hat{\theta}_{jm} + \hat{\gamma}_1 time_{jm}^i + \frac{\hat{\gamma}_2 cost_{jm}^i}{y^i} + \eta_m z_i\right]\right). \quad (8)$$

While the application of this two-stage approach to residential sorting and commuting is new to our knowledge, similar approaches of nesting logsum values from random utility models have been executed by Phaneuf, Smith, Palmquist, and Pope (2008) and Capps, Dranove, and Satterthwaite (2003).

Model closing. The identification of the structural parameters of our model relies on our demand equations conforming to the closing conditions of an equilibrium model of location sorting. These conditions are that 1) The housing market clears: the supply is fixed and housing prices adjust to clear the market; 2) Travel times for driving respond to travel demand by car via the empirical relationship between speed and flow across roads in Beijing;[11] 3) The level of congestion affects individual mode choices which then affect the traffic density on the road, 4) Housing prices and traffic congestion are determined endogenously in the model.

Estimation. To obtain the parameters enumerated in the previous section, we begin by estimating the mode choice model via maximum likelihood estimation to recover consumer preference for travel time and cost. We then construct the logsum value EVi, ∀ j ∈ Mj to be used as an observed housing type attribute (specific to i due to work location) as discussed above. We then estimate the location choice model given the following formulation:

$$V_j^i = \mu_j^i(\theta_2) + \delta_j(\theta_1) + \varepsilon_j^i \quad (9)$$

$$\mu_j^i(\theta_2) = \log(p_j)\, z_i\alpha + \sum_k X_{jk} z_i \beta^k \quad (10)$$

$$\delta_j(\theta_1) = \bar{\alpha}\log(p_j) + X_j\bar{\beta} + \xi_j. \quad (11)$$

The parameters of the model are estimated in two steps following: first, we estimate household-specific parameters (θ_2) and alternative specific constants or mean utilities (δ_j) using maximum likelihood estimation with a nested contraction mapping by matching observed and predicted market shares via the mean utility obtained by inverting shares on each iteration d:

$$\delta_j^{d+1} = \delta_j^d + ln\, S_j - ln\, s_j\,(\delta_j^d\,;\,\theta_2),$$

where S_j are observed market shares for each housing type and s_j are predicted shares constructed by calculating:

$$ln\, s_j\,(\delta_j^d\,;\,\theta_2) = \frac{exp\{V(\delta_j;\,\theta_2)\}}{\sum_k \exp\{V(\delta_k;\theta_2)\}}$$

In the second stage, we estimate mean preference parameters (θ_1) in mean utilities via OLS and IV.

11 We allow travel times to adjust following estimates between travel times and highway density for Beijing reported by Yang *et al.,*(2019) from a regression of changes in speed on changes in the density of vehicles on roads: ∆speed= ε ∆density, ε = −1.1.

Identification. A couple of factors could potentially confound our estimation of the parameters outlined above, so here we lay out our approach to account for this. First, we include house fixed effects (mean utilities), which control for local-specific unobservables and common shocks that could affect traffic conditions. Second, as discussed above, housing prices and the congestion level are determined simultaneously together with individual mode and location choices. Estimation of (11) is therefore confounded by the fact that this simultaneity means that $E(\xi_j\, p_j) \neq 0$. To account for this, we instrument for prices using the average attributes of houses (excluding price and the logsum term) between 1-5 kilometers following Berry, Levinsohn, and Pakes (1995).

4. Findings

4.1 Impacts on traffic congestion

Main results. Table 1 reports the average marginal effect of new subway openings on traffic congestion in Beijing using equation (1). Each entry in this table represents the result of a separate regression, with the dependent variable in the column headings and the functional form of the regression in the row headings. The coefficient reported in each cell is the estimate of the local average treatment effect of the subway opening.

In the first panel, we do not include covariates and take a simple average of the six subway openings for our results. In the second panel of this table, we include covariates that may influence travel patterns: dummies for the day of the week, for extreme weather, for which license plates are excluded from Beijing roads, and for the subway opening that is under consideration. The magnitude and statistical significance of the coefficients in this table are generally stable to the presence or absence of additional covariates. The results of these rows give us the unweighted average effect of one of the six subway openings in Beijing.

In the third and fourth panels of Table 1, we weight observations by the average passenger volumes of the opening lines. Weighting observations by volume is intuitively sensible because we expect the effect of subway openings on transportation patterns to be larger if passenger volume on them is higher. The results of these rows give us the ridership average partial effect of subway openings in Beijing. Specification 4, with both subway line weighting and additional covariates, represents our preferred method of estimating the impact of subway openings on bus traffic and vehicle congestion.

The first two columns give the average effect of new subway openings on total subway traffic and on existing subway lines. The estimates suggest that these openings add sharply to total traffic, but do not diminish traffic for existing lines. Existing subway lines do not appear to change in ridership when new subway lines open. New subway openings also appear to draw away riders from buses, as demonstrated in column 3.

Our estimates of the impact of subway openings on congestion are in columns 4 through 6 of Table 1. We find that subway line openings have a large and statistically significant impact on overall congestion levels in Beijing. Average daily congestion decreased by 0.728 after subway openings in our preferred specification of panel 4, a large and statistically significant decrease from the pre-opening level of 5.408.

Table 1: Regression discontinuity-based results of subway effects on traffic congestion

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
Specification 1: Unweighted estimation						
Subway Open	0.046***	0.007	-0.033***	-0.687***	-0.750**	-0.631**
	[0.015]	[0.012]	[0.009]	[0.253]	[0.297]	[0.270]
R^2	0.794	0.879	0.456	0.296	0.221	0.261
Specification 2: Add covariates						
Subway Open	0.053***	0.001	-0.037***	-0.652***	-0.796**	-0.514**
	[0.011]	[0.014]	[0.010]	[0.221]	[0.298]	[0.188]
R^2	0.901	0.904	0.559	0.493	0.512	0.453
Specification 3: Weight by passenger volume						
Subway Open	0.099***	0.027	-0.024***	-0.851**	-1.139***	-0.571
	[0.015]	[0.015]	[0.010]	[0.319]	[0.358]	[0.345]
R^2	0.776	0.910	0.525	0.294	0.280	0.215
Specification 4: Weight by passenger volume and add covariates						
Subway Open	0.117***	0.028*	-0.023***	-0.728***	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
(N = 475) for all regressions						

Note: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). "All SPV" refers to total subway passenger volume, and "Existing SPV" refers to subway passenger volume less that added on the newly opened lines. The reported coefficient in each cell is the coefficient on "Subway Open," a dummy variable indicating whether the new subway line had opened. All regressions include a third-order polynomial in the predictor. Holidays and weekends are excluded from these models. Regressions with "covariates" contain weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In order to translate these TCI levels into travel times, we utilize the translation summarized in Online Appendix Table A12. The starting average TCI level of 5.408 implies that a route that takes one minute without congestion will instead take 1.71 minutes at this level of traffic. If TCI falls by 0.728, that same trip will take 1.60 minutes, a (0.71-0.60)/0.71 = 15% reduction in delays that applies across the entire city of Beijing.

The point estimate of 0.728 for the decrease in TCI caused by subways has a 95% confidence interval of between -0.080 and -1.375. This corresponds to a reduction in delays of between 2% and 29%.

Strictly speaking, this estimate applies only to the discontinuity, and applies only to weekdays and non-holidays. When we include weekends in our estimates, we find that the standard errors increase so that we cannot conclude statistical significance for the effect of subway openings.

A 15% reduction in congestion is large, and it is reasonable to ask whether those reductions are reasonable relative to the number of new passengers on subways. We compare our results to those of a second policy in Beijing: driving restrictions based on license plate numbers and find that the 0.728 drop in TCI connected with 254,000 new subway passengers is not inconsistent with changes in congestion related to changes in the number of license plates bound by vehicle restrictions.

We also compare our findings to those of Anderson (2014), who uses subway strikes in Los Angeles to examine the effect of shutting down the metro system on congestion. The LA transit system serviced 200,000 passengers per weekday by rail, and 1.1 million by bus. The headline result of Anderson (2014) is that a wholescale shutdown of this system increased delays by 47%, a result about 3 times larger than the 15% we found. So although Los Angeles and Beijing are very different, our estimate and those of Anderson (2014) are not entirely inconsistent.

Column 5 provides our estimates for morning peak traffic congestion; we find that this index decreases by 1.120 in our preferred specification, a very large decrease from the 4.580 pre-opening level and corresponding to a 24% reduction in delay times. Although the point estimates for evening peak congestion suggest that subway openings decrease it, the result is not statistically significant in our main specification. Evening peak congestion (column 6) is generally much higher than morning peak congestion, and it is possible that cars taken off the road during periods of very high congestion are quickly replaced when cars are removed by subway openings.

We next consider graphical evidence on the effect of subway openings on transportation patterns in Online Appendix Figure A5. Levels of each transportation behavior variable clearly drop after each cutoff, although they are not dramatic relative to the underlying variation in the variables.

Daily bus ridership is basically flat in the 60 days prior to subway openings, but this traffic drops in the 60 days following. Although traffic congestion levels are much noisier, they also drop perceptibly after subway openings. Morning TCI also shows a large drop, and this drop is larger than that for evening TCI.

These graphs, in general, align well with the findings from our discontinuity regressions, providing additional evidence that subway openings have an effect on transportation behavior. We test the robustness of our findings using a variety of alternative specifications below.

Expanded sample dates. We limited our sample window to 60 days in our main specification because of the dates of openings 4 and 5, which occurred just four months apart from each other. We can expand our sample period to an interval of six months before and after opening dates by dropping those two lines from consideration. These results are reported in Online Appendix Table A12. In this table, we report the results of our testing from a variety of sample windows.

Our estimates of the effect of subway openings on congestion are generally confirmed by this alternative specification. Standard errors decrease as the window expands, because additional data improve the precision of the estimates. Coefficient magnitudes for congestion peak when the sample period is three months on either side of subway openings, and decline only slightly when the sample period is extended up to six months. Unlike the results in our 60-day specification, testing with larger sample windows suggests that subway openings do reduce evening congestion to a statistically significant degree. Generally, this additional evidence is highly supportive of our main findings: subway openings result in large decreases in congestion in the short-run.

Our estimates of the effect on subway traffic suggest that new subways do add to total subway traffic, but may also diminish traffic from existing lines. Estimates of the effect on bus traffic are less stable, with some estimates statistically indistinguishable from 0 over some sample windows.

Tests of road speed. It would be useful to examine whether our findings on the effects on average Beijing congestion were observed in road speeds from individual roads in Beijing. We were able to obtain access to average road speed data for 22 roads in Beijing during the period September 1, 2014 through March 31, 2015. These data enable us to examine whether the openings of lines 7 and 14e, on December 28, 2014, increased average road speeds for these roads. We perform this test using equation (1), where the dependent variables are the natural logarithm of daily average road speed of a given road during morning rush hour and evening rush hour. We add the same covariates as rows 2 and 4 of Table 1 in our specification, including a third order flexible polynomial.

We report the results of these regressions in Online Appendix Figure A6. The X-axis of this figure is the distance from the midpoint of the road to either subway line 7 or subway line 14e, whichever is closer. The top panel of this figure examines the effect of subway openings on morning average road speed. The point estimates are consistently positive, indicating that average road speeds tended to improve after the subway lines opened. The bottom panel of this figure examines the impact of the subway openings on evening average road speed. Evening road speed of roads close to the subways tended to improve after subways opened, with a decaying effect as the distance between the road and the newly opened subway lines increases.

These results are basically supportive of our main findings. Morning road speeds overall do tend to increase, suggesting that the average decreases in TCI we found earlier are reflected at the individual road level. For evening traffic, increases in road speed are larger close to subways, but decay in roads farther away. This heterogeneity helps explain why the point estimates of the effect of subway openings are negative but are statistically indistinguishable from zero in some specifications.

Alternative specifications. We test the robustness of our results from our regression discontinuity specification. Our first concern involves the timing of subway openings: many openings coincide with holidays such as the calendar New Year. Although we drop holidays from our regressions, it is possible that travel around holidays is lower, because travelers leave Beijing early or end vacations late. We drop all observations within three days of a holiday, reasoning that the impact of most early departures or late returns is likely to occur within three days of holidays. We report our results in the first panel of Online Appendix Table A13, using specification 4 from Table 1. Dropping surrounding days appears to have limited effect on the basic narrative, with subway openings still playing a strong role substituting for bus traffic and lowering average congestion and morning peak congestion.

Related to this concern, we address the possibility that seasonality in passenger volumes explain our results. We create four placebo comparison periods using other portions of daily travel behavior data available between 2009 and 2014. In each of these comparison periods, the dates match those of one of the six sample periods, but they occur in years where no subway opening occurred. We include graphs summarizing these results in Online Appendix Figure A7. There is no discontinuity observed in the number of subway passengers, the bus passenger volume, or in any of our three measures of congestion. This placebo test supports the idea that subway openings rather than seasonality drive our RDD results.

We also address the possibility that other travel policies enacted in Beijing explain our results. For example, the Beijing license plate lottery began to curb the number of new cars, starting on January 1, 2011. In addition, a major adjustment of taxi fares occurred in June 2013. In this check, we remove subway openings 2 and 5 and re-estimate the model. Our results are reported in panel 2 of Online Appendix able A13. Again, the pattern of results is very similar.

We address the possibility that any single subway opening explains our results. We remove each subway opening in turn in panels 3 through 8 of Online Appendix Table A13. The results are very similar, with decreases in congestion observed in every specification. The point estimate of the effect on evening peak traffic is negative in every specification, but not statistically significant.

We address the possibility that our results capture seasonality in travel behavior. This is of particular possible concern because government officials may want to take advantage of seasonal dips in transportation volume in order to artificially inflate the efficaciousness of subways on congestion. We augment our regression with weekly fixed effects. The benefit of this is allowing us to examine within-week variation due to subway openings, removing some seasonality from the data. The cost of this is that two of the six subway openings do not overlap weeks with the other four; as a result, we de-seasonalize only four of the six openings.

We report results in the last row of Online Appendix Table A13. This specification largely confirms qualitatively our prior results: subway openings result in decreases in bus traffic and overall congestion. For many of the dependent variables, this specification actually increases the point estimate of the effect.

We next address the robustness of our main specification. Our main specification used 60 days on either side of new subway openings as the window; we vary this period to see whether smaller sample windows will affect our results. We first limit the sample to 30 days, then 45 days, and 60 days, and report our results in Online Appendix Table A14.

The direction and general magnitude of our coefficients remains essentially intact as the sample window changes. The exception is bus traffic, which has an estimate statistically indistinguishable from zero when the sample window is 45 days. Standard errors expand as the sample shrinks because lower amounts of data adversely affect the precision of the estimates.

We also examine whether alternative polynomial forms affect our results in Online Appendix Table A15. Our main specification relies on third-order polynomials, so we compare our results with other orders of polynomials. Qualitatively speaking, our main results hold true with each order of polynomial. Overall congestion and morning congestion drop significantly, while evening congestion is indeterminate.

4.2 Impacts on air quality

In this section, we first present the estimated impacts of subway expansion on air quality using the IV method and the DID method in the first two subsections. We then present the results from a benefit-cost analysis based on back-of-the-envelope calculations.

4.2.1 Estimates based on network density

Online Appendix Table A16 shows the OLS results and Table 2 shows the IV results, both using the continuous density measure shown in Equation (2). The key variable is the standardized subway network density. We sequentially add weather variables, wind conditions, a rich set of location and time fixed effects, and the driving restriction policy as control variables. We look at the OLS results presented in Online Appendix Table 16 first. Column (1) does not have monitoring station fixed effects, and the result shows a positive correlation between subway density and the level of air pollution. This result is likely driven by the fact that the city center, where the subway network is denser, tends to have higher pollution levels. Once monitor fixed effects are included, the results show that higher subway density is associated with a lower level of air pollution. This negative relationship is robust across columns (2) to (4). Column (3) adds monitor fixed effects interacting with the driving restriction policy, while column (4) further includes a monitor-specific time trend. Adding the monitor-specific time trend helps to alleviate the concern about the endogenous location of subway lines. Subway lines may tend to be placed in areas with faster projected growth in economic activities (and hence more air pollution); without controlling for this, the impact of subway expansion on air quality would be underestimated, as confirmed by the results in columns (3) and (4).12

The results from the full model (column (4) of Online Appendix Table A16) suggest that a one standard-deviation increase in subway density reduces the air pollution level by 1.5 percent. This estimation exploits the variation in network density and air pollution across space and locations. It can be interpreted as the longer-term impact, when we compare it with estimates from the DID framework presented in the next section or from the literature, which typically relies on a shorter time window around the intervention to address confounding factors.

The weather variables have intuitive signs: high temperature and humidity are associated with a higher level of air pollution while rainfall/snow and wind are associated with a lower level of air pollution. High temperature can lead to faster formation of ground-level ozone and fine particulate matter while high humidity (without precipitation) makes it difficult for the natural air current to dissipate the pollutants. Precipitation in the form of rainfall or snow, as well as high wind, can help pollutants dissipate more quickly.

We address the potential endogeneity of network density measure using IV in Table 2. Column (1) is identical to column (4) in Online Appendix Table A16 to facilitate comparison. Column (2) instruments for the density variable with a hypothetical density measure based on the 2003 subway planning map and uses the actual opening date of

[12] We have also tried two alternate monitor-specific time trends: time squared and time cubed. The OLS results are robust to the order of the time trend, we find similar estimates with monitor-specific squared time trend and monitor-specific cubed time trend.

each line. The impact from two stage least square (2SLS) is slightly larger in magnitude than that from OLS. Column (3) uses a random opening date during a six-month window around the observed opening date to construct the IV. This helps to address the concern that policymakers may choose the opening date partly based on the projected pollution level. In practice, the opening of a new subway is often celebrated with a ceremony at which high-level government officials from both the Beijing municipal government and the central government are present. Seven out of the 10 opening dates in our sample fall in the last few days of a calendar year. In addition to the coincidence of celebrating a new subway line opening together with the beginning of a new year, this choice of dates is also likely due to the fact that it is easier to gather high-level government officials during the public holidays.

Online Appendix Table A17 translates the parameter estimates of the IV regression with observed opening dates into the impact for each subway line. To estimate average subway density in Beijing, we calculate the subway network at the Traffic Administration Zone (TAZ) level.[13] Online Appendix Figures A8 and A9 map the subway network density at the TAZ level at the end of 2007 (the year before our study period), 2009, 2011, 2013, and 2016. The subway network, which is denser at the city center, has been expanding rapidly with openings of new subway lines. For example, the opening of Line 6 (opened on December 30, 2012) increases the population-weighted density by 0.12 overall, which in turn leads to a 0.24 percent decrease in air pollution level. In the aggregate, the total 14 lines built from 2008 to 2016 result in a 1.01 percent decrease in air pollution in Beijing. Our estimates of the pollution reduction effect are smaller than that of Gendron-Carrier et al. (2018), who find a four percent reduction in air pollution after the opening of a new subway system. However, the majority of new subway systems considered in Gendron-Carrier et al. (2018) were the first subway lines in their corresponding cities, which could explain the larger estimated impacts than those in our case. In addition, studies using the DID or the regression discontinuity method tend to have larger estimates (Chen and Whalley 2012; Zheng et al. 2017), as these estimates may capture a shorter term and more local impact than ours. This is consistent with our analysis using the DID method below, which shows a larger impact than the estimate based on the continuous density measure.

[13] The city of Beijing is divided into 1911 Traffic Administration Zones (TAZs) for the purpose of city planning. Each TAZ has similar population size so the average subway density at the TAZ level is roughly equivalent to the population-weighted average of the density at the district level.

Table 2: IV: The impact of subway expansion of air pollution

(a) Standardized non-weighted density			
	(1)	(2)	(3)
Dependent variable: ln(*Air Pollution*)	OLS	IV	IV
		Second Stage	
$Density_{it}/\sigma$	-0.015***	-0.020***	-0.028***
	(0.003)	(0.004)	(0.009)
Random Opening Dates		N	Y
		First Stage	
$Density_{it}/\sigma$ (2003 Planning)		0.789***	0.651***
		(0.004)	(0.012)
F-stat		48808	3160
(b) Standardized ridership-weighted density			
	(1)	(2)	(3)
Dependent variable: ln(*Air Pollution*)	OLS	IV	IV
		Second Stage	
$\widetilde{Density}_{it}/\sigma$ (ridership weighted)	-0.026***	-0.024***	-0.035***
	(0.007)	(0.005)	(0.011)
Random Opening Dates		N	Y
		First Stage	
$Density_{it}/\sigma$ (2003 Planning)		0.655***	0.520***
		(0.004)	(0.012)
F-stat		57069	2605

Note: The last two column report results from IV regression where the dependent variable is ln(Air P ollution) and the key explanatory variable for Panel (a) is the standardized subway network density, $Density_{it}/\sigma$. Panel (b) shows results with the key explanatory variable as density measure using line ridership as extra weights for the subway stations, D ensityit/σ. Column (2), (3), (5) & (6) report the result from IV regressions with different specifications. The instrument is the subway network density based on the 2003 subway plan map. Column (2) and (5) use the same opening dates for actual subway system and the IV. Column (3) and (6) assign random opening dates for lines in 2003 plan as the 3 months before or after the real opening dates. The unit of observation is monitor-day. All columns control for the daily weather variables: temperature (C0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed , dummies for rain, snow, storm, fog; the time fixed effects: day-of-week, quarter-of-year, year, holiday-of-sample dummies; spatial fixed effects: dummies for air pollution monitoring stations and the interactions with the time trend and driving restriction policy dummies. Parentheses contain standard errors clustered at the day level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

4.2.2 Difference-in-differences estimates

Online Appendix Table A18 presents the results from the basic DID model (Equation (3)). The results across columns exhibit similar patterns to those in Online Appendix Table A16. With the absence of monitoring station fixed effects in columns (1) to (3) of Online Appendix Table A16 air pollution level is positively associated with subway opening. After controlling for monitor fixed effects, Columns (4) to (6) provide similar estimates of the effects of subway opening on air pollution based on the DID model.[14] The results from column (6) suggest that within a 60-day time window after a subway line's opening, the monitors in the vicinity (within 2km) of subway stations exhibit a 7.7 percent reduction in air quality compared to the monitors outside the 20km radius.

The DID specifications produce relatively larger impact estimates compared to those from the framework based on continuous density measures, likely for two reasons. First, the DID method focuses on a shorter-time window, while the method with density measures relies on variation during the whole data period. Thus, the DID estimates should be viewed as shorter-term impacts. Second, the DID method estimates the impacts of subway expansion on the areas within a 2km radius of new subway lines which are likely larger than the city-wide effects estimated by the method with network density measures.

Online Appendix Table A19 reports regression results using different time windows (from 10 to 180 days) before and after the opening dates. The estimates are not statistically different across 40- to 100-day windows (column 4 to 10). When we increase the window to 110 days and longer, however, the average effect seems to fade away. This is consistent with the notion that it may take some time for commuters to adjust their travel modes in the short term and hence for the impact on air pollution to be materialized. In the longer term, reduced traffic congestion could lead to additional driving demand, mitigating the initial reduction of air pollution. This dynamic is consistent with traffic diversion in the short-term and with induced traffic demand in the longer-term, as discussed in the introduction.

Online Appendix Table A20 shows the effect under a continuous measure of the time variables. We interact the treated group indicator with the linear and quadratic term of days post-opening, respectively. We also compare the specifications under two different time windows (60 days and 120 days). The results from our model specifications with the quadratic term of days post-opening (columns 2 and 4) suggest that the effect of subway opening on air pollution is non-linear. The subway opening begins to have a negative effect on air pollution after approximately 15-20 days; the magnitude of the effect then increases at a decreasing rate, with a turning point being around 50-60 days, after which the effect diminishes.

Online Appendix Table A21 presents the DID specification which accounts for the number of subway stations in the vicinity of treated monitors. The result shows that one additional subway station added to the vicinity of a monitor reduces air pollution by 2 to 4.1 percent, depending on model specifications. Compared to the IV method based on the network density measure, the DID method yields qualitatively the same results but considerably larger point estimates. Take the previous example of Line 6. The opening of Line 6 improves air quality in Beijing by 0.70 percent (assuming no effects on buffered locations) to 6.04 percent (assuming the buffered locations have the same impact as the treated locations). This comparison reflects the interplay of the two countervailing forces: the traffic division effect of public transit investment (the Mohring effect), and the induced

[14] In appendix table A18, we cluster the standard errors at the day level. To address the concern auto-correlation issue, we use the two-way clustering at the monitor level and day level, as a robustness check. The two-way clustered standard errors are larger for all specifications, but the subway effects on air polution are still significant at the 5% level for the DID specifications (Columns 4-6).

demand effect. The second channel takes longer to occur and dampens the positive impact on air quality improvement observed in the short term. Nevertheless, our estimates suggest that the first channel is the dominant force in the longer run.

4.3 Impacts on travel mode, housing prices, and welfare

We now lay out the first estimates of demand for housing based on commuting availability for Beijing. We begin by presenting estimation results for the mode choice model. Based on the parameters from that model, we then construct the log sum expected value of commuting options based on place of work and home location for households and estimate their housing demand.

4.3.1 Model estimation

In Online Appendix Table A22, we present estimates from a multinomial logit model of mode choice over walking, biking, driving, subway and bus. We include alternative specific constants for each mode except walking, and include additional controls from columns (1)-(4). Comparing columns (1) to (2)-(4) in panel A, it is clear that the estimates change substantially when trip distance is included as a control. Including it makes the coefficient for pecuniary cost negative, which is consistent with intuition. Because the attractiveness of a particular mode will depend upon the length of the trip, if we do not control for this, it may be the case that we are picking up the fact that modes for which there is higher cost (driving, but also subway and bus) are going to be more attractive for longer trips. Once this is included, he results remain fairly consistent as we add respondent (age, sex, education) and household characteristics (size, cars, workers).

In panel B, we then enumerate the implied value of time by taking the ratio of time and cost coefficients from our preferred specification in column (4) of panel A.[15]

We now turn to the results of estimating the two-stage residential sorting model described earlier which utilize estimates from the mode choice model to construct the logsum expected value of commuting options for a household at a given location. Panel A of Online Appendix Table A23 reports the first stage estimates of a maximum likelihood model using a sampling of 20 available properties (plus the chosen one) to construct the choice set. In column (1), we report our preferred estimates, which have a negative sign on the housing price as would square with intuition and a postive sign on the logsum, suggesting that in locations with better commuting options households are more likely to locate there. When we run the same estimation without the logsum, however, we can see that the housing price becomes more negative.

Turning to the second stage, we can see that OLS estimates in columns (1) and (2) seem to underestimate the price coefficient relative to the IV model, suggesting that unobserved housing attributes may upwardly bias our OLS estimates. The coefficient on distance to the city center is consistent with declining pricing gradients moving out from the city center. Higher unit sizes have seemed to increase the probability a house is chosen, but looking back at panel A, this increases with a buyer's age, perhaps because for households that eventually have a child or family members live with them.

[15] These estimates imply a value of time that is 57% of a worker's hourly wage, which is in line with what much of the transportation literature has found (Small, 2012)

4.3.2 Counterfactual simulations

We now utilize the estimates from our model of household and mode choice to consider three policy scenarios that help to understand how the series of transportation policies enacted in Beijing have affected households and also benchmark them against a policy that would charge a congestion fee to drive on the road. Specifically, we construct simulations of three alternatives: household behavior in the absence of Driving Restriction Policy (Counterfactual), cordon-style congestion charge within 5th Ring Road and the expansion of subway from 2008 to 2014 network.

Simulation approach. In order to simulate these alternative policy scenarios, we alter the inputs to the logsum equation (8) and as a result also for the indirect utility for housing from equation (11). We focus on observations in the last year of our sample, 2014. To simulate the absence of a driving restriction, we replace the alternative specific constant for driving for travel survey respondents inside of the driving restriction area (5th ring road) with those outside of it reflecting the fact that driving is now available to them without penalty. To simulate the effects of expanding the subway network, we replace the times and distances of subway commuting for households based on the same locations from the 2008 subway network. Finally, we consider a 50 RMB congestion cordon within the 5th ring road by increasing the cost of driving for all households with home or work within this road.

For the following simulations, we assume "closed city" with no change in population and a fixed housing supply consisting of the units in our sample. We also assume that the transportation network is fixed apart from the policies described above. The simulation algorithm described below begins with an initial observed price vector and road congestion vector, which will be endogenously determined by the algorithm on each iteration.

After setting the policy vector as defined above, the outer loop of the algorithm allows households to adjust mode choice in response to the policies described. We then reconstruct the logsum based on new travel conditions. Then within an inner loop we allow households to choose a new housing location based on this new logsum expected value. Based upon the new pattern of demand, we resolve for a new price vector that equates housing demand with fixed supply. Given a new pattern of demand we also reconstruct the implied driving in Beijing given mode choice from the inner loop. With that driving pattern, we adjust driving travel times to reflect congestion for driving separately between district-ring road regions. Because transportation policies do not just affect households buying a house (a fraction of all residents), but all commuters, we approximate district-ring road populations and use mode choice probabilities to predict mode switching for these households to construct a new aggregate travel demand pattern for driving D_j.[16]

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[16] Let r be the work district-ring road region for a household, then the total number of drivers traveling from home district-ring road j is $D_{jr} = \hat{d}_{jr} + Pr[mode_i = drive]_{jr} \cdot d_{jr}^{other}$, where $\hat{d}_{jr}$ is the predicted drivers buying homes and commuting from j to r, and d_{jr}^{other} are non-homebuyers. We calculate the later as $d_{jr}^{other} = \frac{d_{jr}^{travsurvey}}{d_j^{travsurvey}} \cdot d_j^{Beijing} 0$, which applies the share of households in the travel survey traveling to r from j to the population that lives in region j. We approximate the latter by overlaying population estimates by $jiedao$ (neighborhood) and overlaying this on district-ring road regions.

Finally, based on the new driving demand pattern D_{jr}, we then allow driving travel times to respond to the new traffic pattern. Using a speed-density response of -1.1 estimated in Li, Purevjav and Yang (2019), we adjust the implied travel speed and therefore time based upon the number of drivers traveling between district-ring roads regions D_{jr}. We then repeat the inner loop until convergence and then repeat the outer loop until convergence.

Simulation results. Online Appendix Table A24 reports the results for simulating the three policy scenarios outlined above while only allowing mode choice (and congestion) to change but not household location. Column (1) reports changes in mode shares and speed for households above and below the median sample income for the counterfactual scenario where there is no driving restriction, no congestion change and no subway expansion. By adding the driving restriction, it is clear that driving becomes less popular, more so above median income households (having a higher share of car ownership), and speeds raise by roughly 2 kph. The congestion charge also decreases driving, but by less for the Above group as many will still drive but pay the congestion charge. Finally subway expansion disincentivizes driving, increases subway use and decreases the use of some other modes. The effect on speeds is much smaller.

We can compare this with simulations for the same policy scenarios, but where we allow households to also move location. In this case, as shown in Online Appendix Table A25, we can see that under the driving restriction, there is a larger response to the driving restriction, in part because households can move to locations where their ability to not drive is greater, which is consistent with Above households moving closer to the subway and to work. Responses to the congestion charge are also larger for driving, and we can see that this has the effect of allowing Above households to live farther from work and the subway, which may reflect the combination of a desire to live closer to other amenities, consume more housing and pay the toll to drive a slightly longer distance. The subway expansion in column (4) has the effect of dramatically decreasing the distance to the subway for Above households, but not for Below, suggesting sorting as the former displaces the latter in locations around subways.

In Online Appendix Figure A10, we plot price gradients from both sets of simulations with distance from the nearest subway. In panel (a), we compare simulations with the 2008 subway network relative to those with the 2014 network. The fact that the former is steeper suggests a greater premium associated with proximity to the network, which may reflect the fact that on average households are closer to a subway under the 2014 network, so the premium would be lower. In panel (b), we compare price gradients under the driving restriction and the congestion charge which prove to be much steeper, reflecting higher demand for proximity to a subway station when driving is relatively costly.

Finally, we report in Table 3 welfare estimates that compare the welfare effects of each policy relative to the no policy baseline allowing for just travel mode and also travel mode and housing sorting. The no policy baseline describes the scenario of no driving restriction, no congestion charge, and with subway network observed in 2008. Welfare estimates are based on consumer surplus and do not include revenue recycling or reflect direct costs of enforcing the driving restriction, implementing the congestion charge or paying for subway expansion.

Apart from subway expansion, all of the policies lower welfare, for the driving restriction because households would like to drive if they could and for the congestion charge because they do not receive the revenues back. Costs are larger to high income households likely because these are the households that are likely to drive without the policy. For both the driving restriction and the subway expansion, allowing housing location sorting to occur increases welfare because households are able to better adjust to lower costs of commuting and benefits of location. The exception to this seems to be for low income households under the congestion charge, which may reflect effects on the cost of housing. In future work, we plan to add the constraint of balanced budget for the government (through revenue recycling in the congestion charge case, and tax in the subway expansion case) in the welfare calculation. In addition, we would like to introduce a constraint on the impact of congestion relief (e.g., different policies reach the same level of congestion) and compare the welfare impacts of these policies on the basis of achieving same congestion relief.

Table 3: Simulation results: welfare effects

	(1)		(2)		(3)	
Δ Consumer Surplus in 1,000s 2010 RMB	**Driving Restriction**		**Congestion Charge**		**Subway expansion**	
	Household Income Relative to Median					
	Below	**Above**	**Below**	**Above**	**Below**	**Above**
Travel Mode Only	-2.81	-14.12	-3.33	-12.95	1.08	3.21
Travel Mode & Location	-2.68	-11.54	-3.56	-10.81	1.39	5.41

5. Benefit-cost analysis

This section presents a back-of-the-envelope analysis on the benefit of subway expansion through two channels. The first benefit is on human health including both mortality and morbidity from improved air quality. The second benefit comes from congestion relief and the value of saved travel time for commuters.

Our empirical analysis finds that subway expansion leads to statistically significant improvement in air quality. Online Appendix Table A17 shows the estimated air quality improvement due to each subway line based on the benchmark specification (based on the IV results in Table 2). The population weighted air quality improvement ranges from 0.02 percent by Line 16 opened on December 31, 2016 to 0.24 percent by Line 6 opened on December 30, 2012. Recent literature from both epidemiology and economics has shown that the long-term exposure to airborne particulates can lead to elevated mortality especially among infants and morbidity due to cardiorespiratory diseases (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Greenstone and Hanna, 2014; He, Fan and Zhou, 2016; Knittel, Miller and Sanders, 2016; Ebenstein *et al.*, 2017)

To calculate the mortality impact of subway expansion, we take the estimates from Ebenstein et al. (2017) that study the impact of long-term exposure to airborne particulate matter on mortality using a regression discontinuity design. They find that a 10-μg/m3 increase in PM10 increases cardiorespiratory mortality by 8 percent; this impact varies across age cohorts but not across gender. Following the analysis in

Barwick *et al.*, (2018) to monetize the mortality impact, the mortality cost amounts to $13.38 billion across the Chinese population from a 10-μg/m3 increase in PM10, or $64.9 per household in Beijing when adjusted for the Beijing per capital income (in 2015 dollars). The morbidity cost of air pollution comes from Barwick *et al.*, (2018), who provide the first comprehensive analysis of the morbidity cost in China based on the universe of credit and debit card spending. They find that the morbidity cost from a 10-μg/m3 increase in PM2.5 is $20.2 (in 2015 dollars) per household for China.

The congestion relief benefit comes from the value of the saved commuting time. We estimate that each new subway line reduces travel delay by an average of 15 percent based on the subway lines that opened between 2009 to 2015. The Beijing Annual Transportation Report shows that the average traffic delay time is around 20 minutes per hour. We assume that these delays occur during the peak hours (7am-9am and 5pm-7pm) on the weekdays and that approximately two million commuters (who travel by cars and buses) are affected. The value of time (VOT) for automobile travel is often assumed to be half of the market wage (Parry and Small, 2009), which is 62.98 Yuan per hour ($9.5 per hour) based on the monthly wage of 10,077 Yuan.

Panel (a) of Table 4 presents the benefit-cost calculations during a 10-year period after the opening of each subway line. The cost includes both the upfront construction cost and the operating cost (Column 1). We discount the operating cost and the benefit at a 5 percent annual discount rate. The total cost from all the subway lines during the sample period is $56.3 billion (with the construction cost being $46.7 billion). The health benefit amounts to $0.64 billion (Column 2), or 1.13 percent of the total cost (Column 4), while the benefit from congestion relief is $26.9 billion (Column 6), or 48 percent of the total cost (Column 8). Panel (b) of Table 4 presents the cost-benefit calculations during a 20-year period where the benefit from health and congestion relief accounts for 1.38 percent and 58 percent of the total cost, respectively. The analysis suggests that the health benefit from improved air quality is a relatively small portion compared to the overall benefit of subway expansion. However, our benefit estimates in Columns (2), (4), (6), and (8), are conservative for three reasons. First, the mortality benefit is based on the Value of a Statistical Life (VSL) of $2.27 million (in 2015) from (Ashenfelter and Greenstone, 2004), rather than the central estimate of $8.7 million figure recommended by the U.S. EPA. Second, the value of time is assumed to be 50 percent of the wage, rather than 100 percent of the hourly wage (Small, 2012; Wolff, 2014). Third, the benefit calculation includes neither the benefit from improved commute reliability nor the benefit from a larger choice set of travel modes (Small, Winston and Yan, 2005).

We then calculate an upper bound of the health benefit and congestion relief benefits in 10-year and 20-year respectively, presented in Columns (3), (5), (7), and (9). These estimates are based on the VSL of $8.7 million from the U.S. EPA and the VOT of 100 percent of hourly wage in Beijing. At the upper bound, the health benefit amounts to $2.01 billion or 3.57 percent of the total cost while the benefit from congestion relief is $53.71 billion or 95.34 percent of the total cost during a 10-year period. During a 20-year period, the upper bound of benefits from health and congestion relief accounts for 4.36 percent and 116.41 percent of the total cost respectively. Together, the total benefits from health and time saving alone exceed the costs during a 20-year timeframe, recognizing that subway systems could have a life span of at least several decades or over 100 years.

Table 4: Benefit-cost analysis of subway expansion

Opening Date	Total Cost Billion $	Health Benefit Billion $		Health Benefit % of Cost		Congestion Benefit Billion $		Congestion Benefit % of Cost	
		lower VSL=2.3	upper VSL=8.7	lower VSL=2.3	upper VSL=8.7	lower VOT=0.5	upper VOT=1.0	lower VOT=0.5	upper VOT=1.0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) 10 Years of Operation									
Jul 19, 2008	5.69	0.08	0.26	1.45	4.58	2.69	5.37	47.28	94.46
Sep 28, 2009	3.61	0.06	0.20	1.79	5.65	2.69	5.37	74.52	148.66
Sep 30, 2010	7.05	0.08	0.25	1.14	3.61	2.69	5.37	38.16	76.23
Sep 31, 2011	5.19	0.03	0.10	0.60	1.90	2.69	5.37	51.83	103.56
Sep 30, 2012	10.37	0.13	0.42	1.28	4.04	2.69	5.37	25.94	51.80
May 5, 2013	3.15	0.03	0.08	0.84	2.66	2.69	5.37	85.40	170.51
Sep 28, 2013	1.96	0.02	0.05	0.77	2.43	2.69	5.37	137.24	274.73
Sep 28, 2014	11.58	0.15	0.47	1.28	4.04	2.69	5.37	23.23	46.39
Sep 26, 2015	2.94	0.04	0.14	1.49	4.70	2.69	5.37	91.50	182.43
Sep 31, 2016	4.81	0.01	0.04	0.26	0.81	2.69	5.37	55.93	111.73
Total	56.34	0.64	2.01	1.13	3.57	26.90	53.70	63.10	95.34
(b) 20 Years of Operation									
Jul 19, 2008	6.21	0.13	0.40	2.05	6.47	4.15	8.29	66.83	133.50
Sep 28, 2009	4.14	0.10	0.32	2.41	7.62	4.15	8.29	100.24	200.39
Dec 30, 2010	7.57	0.12	0.39	1.64	5.18	4.15	8.29	54.82	109.51
Dec 31, 2011	5.71	0.05	0.15	0.84	2.67	4.15	8.29	72.68	145.18
Dec 30, 2012	10.89	0.20	0.65	1.88	5.94	4.15	8.29	38.11	76.10
May 5, 2013	3.67	0.04	0.13	1.11	3.52	4.15	8.29	113.08	225.65
Dec 28, 2013	2.48	0.02	0.07	0.94	2.96	4.15	8.29	167.34	334.42
Dec 28, 2014	12.10	0.23	0.72	1.89	5.96	4.15	8.29	34.30	68.51
Dec 26, 2015	3.47	0.07	0.21	1.95	6.16	4.15	8.29	119.60	239.04
Dec 31, 2016	5.33	0.02	0.06	0.36	1.13	4.15	8.29	77.86	155.51
Total	71.22	0.98	3.11	1.38	4.36	41.50	82.90	84.49	116.41

Note: All the monetary terms are in 2015 dollars and discounted by an annual discount rate of 5%. The total cost includes both the construction cost and the operating cost. The construction cost accounts for 82.9% of the total cost during a 10-year period for the lines in the sample period and 65.6% for the period of 20 years. The health benefit includes the saving from mortality and morbidity costs. The lower bound health benefit calculations are based on the Value of a Statistical Life (VSL) of $2.3 million (in 2015) as in Ashenfelter and Greenstone (2004). The upper bound health benefits are based on the central estimate of $8.7 million as recommended by U.S. EPA. The savings from congestion relief is calculated based on the reduced time delay by subway opening using estimates from Yang *et al.,* (2018a). The lower bound of congestion cost saving assumes the value of time (VOT) to be 50% of the wage, and the upper bound assumes 100% of wage as the VOT.

6. Conclusions and recommendations

Employing big data from a variety of sources and different empirical methods, we examine in this study the effects of rapid subway expansion in Beijing on traffic congestion, air quality, travel modes, housing prices, and welfare. We also analyze the cost effectiveness of subway expansion.

Using a sharp time-series regression discontinuity (RD), we investigate how six subway openings in Beijing affect vehicle congestion. We find that reductions in congestion improve TCI by 0.728, reducing average daily driving delays by 15% across the six openings. This result is robust across a broad set of specifications and potential alternative explanations. We also find that subway openings play an important role in reducing morning rush hour traffic.

To estimate the effects of subway expansion on air quality, we leverage fine-scale air quality data and the rapid build-out of 14 new subway lines and 252 stations in Beijing from 2008 to 2016. Our main empirical framework examines how the density of the subway network affects air quality across different locations in the city during this period. To address the potential endogenous location of subway stations, we construct an instrument based on historical subway planning, long before air pollution and traffic congestion were of concern. Our analysis shows that an increase in subway density by one standard deviation improves air quality by two percent and the result is robust to a variety of alternative specifications including the distance-based difference- in-differences method.

To examine the effects of subway expansion (in combination with other transportation policies) on travel mode, housing prices and welfare, we develop and estimate a residential location sorting model to examine the interactions of transportation policies and household sorting. The sorting model incorporate commuting decisions and generates equilibrium predictions of household locations under different transportation policies. We estimate the model parameters using a large household travel survey and rich housing transaction data in Beijing. We then use the estimates from this model to simulate a series of counterfactual policies to assess the effects of Beijing's vehicle restriction policy and public transportation expansion. The analysis illustrates the importance of incorporating travel mode choices in household location decisions and the importance of understanding sorting behavior in designing effective transportation policies. We also demonstrate how equilibrium sorting can result in lower income households being pushed farther away from public transit, lowering their welfare.

We conduct a back-of-the-envelope analysis on the benefit of subway expansion through two channels. The first benefit is on human health including both mortality and morbidity from improved air quality. The second benefit comes from congestion relief and the value of saved travel time for commuters. The results suggest that the benefits from health and congestion relief accounts for 1.38-4.36 percent and 58-116.41 percent of the total cost, respectively, during a 20-year period. We note that the benefit calculation includes neither the benefit from improved commute reliability nor the benefit from a larger choice set of travel modes (Small et al. 2005). Recognizing that subway systems could have a life span of at least several decades or over 100 years, our analysis suggests the total benefits from health and time saving alone would exceed the costs of subway expansion.

We find that subway expansions in Beijing significantly improved air quality, reduced traffic congestion, and affected travel modes and housing prices. Cost-benefit analysis suggests that most of the cost from subway expansion needs to be justified from traffic congestion relief and other economy-wide impacts, rather than improved air quality. Although different transportation policies can achieve the same level of traffic congestion reduction, they could have very different impacts on the housing market and the spatial pattern of household locations.

To combat traffic congestion and air pollution, the Beijing municipal government has been investing heavily in transportation infrastructure such as buses, roads, and subway lines. During 2002 to 2014, the total investment in subway lines amounted to nearly 400 billion yuan (about USD 65 billion). Despite the huge investment in subway infrastructure in Beijing and other major cities in China, rigorous evaluation of the social and economic impacts of subway expansion was lacking. Our research fills this void by quantifying the extent to which subway expansion works in addressing traffic congestion and air pollution problems and investigating whether the benefits of the investments can justify their costs. Our research provides important evidence for the central and local governments of China to justify the use of public funds in subway infrastructure among competing programs and to select cost-effective policies in reducing traffic congestion and air pollution. This is also an important first step toward understanding the impacts of these infrastructure investments on broad social and economic issues such as economic growth, income inequality and social welfare.

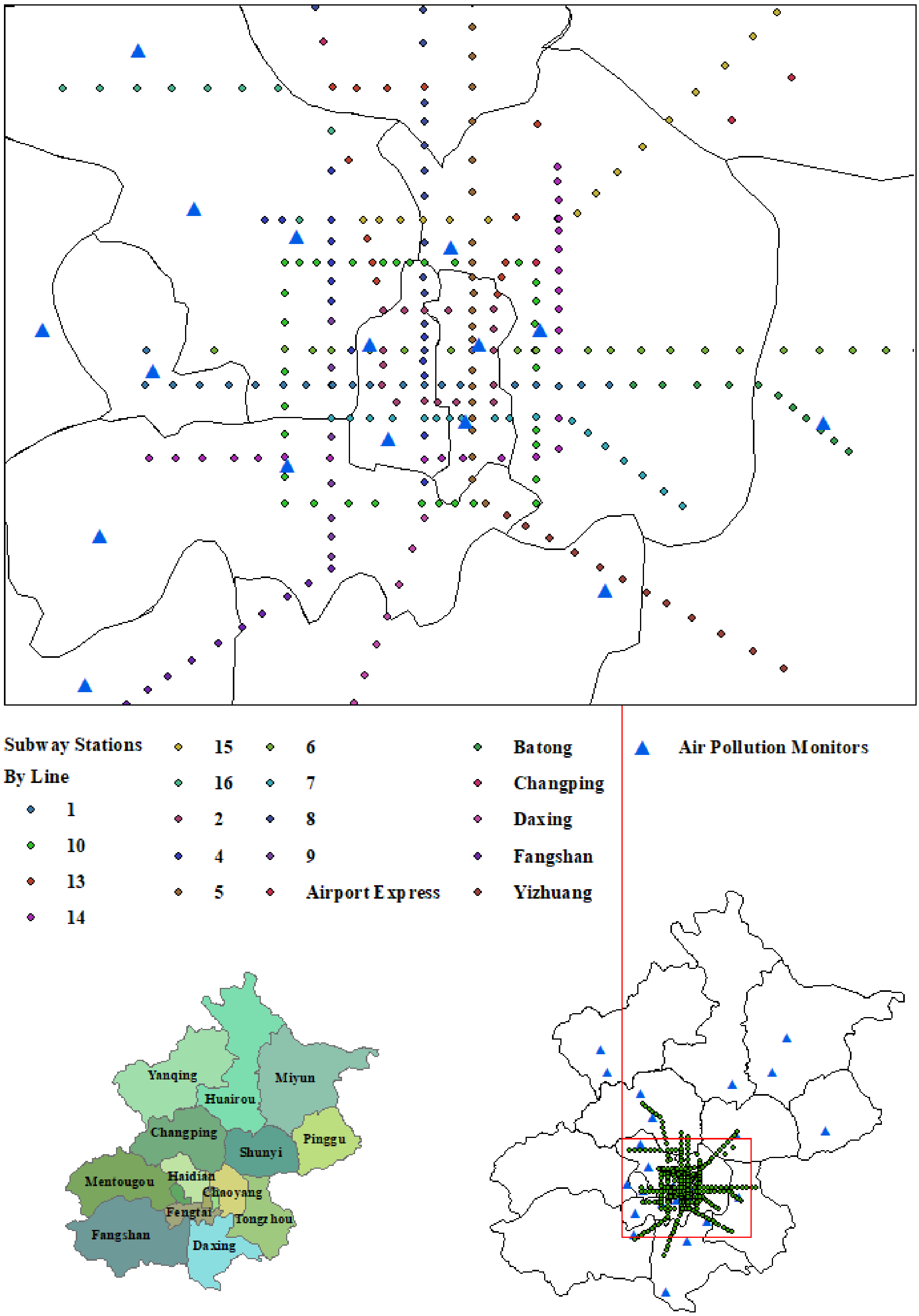
Our results are most externally valid in large, dense cities that have sparse subway systems in place and are considering expansions. China alone has 160 cities that have a population greater than 1 million people. As rapid urbanization in developing countries has become a global trend, our study also provides useful policy recommendations for other developing countries. This is particularly true for India, where PM2.5 concentrations are similar to China and traffic congestion in major cities is getting worse.

To distill the findings and summarize the policy implications:

- The benefit of subway expansion on air quality improvement is modest while the benefit through congestion is at least one magnitude larger. Most of the cost from subway expansion needs to be justified from traffic congestion relief and other economy-wide impacts.
- Transportation policies could have important impacts on the housing market. Both driving restriction and congestion pricing increase the price premium of properties close to subway, the impact of the subway expansion is opposite. In addition, driving restriction and subway expansion pushes low-income households further from subway and work location, while road pricing does the opposite
- While different transportation policies can be designed to reach the same level of congestion reduction, the impact on urban spatial structure and the distributional consequences can be drastically different. Given the important differences in policy impacts, it is crucial for policy makers to understand the distributional and equilibrium effects of different transportation policies.

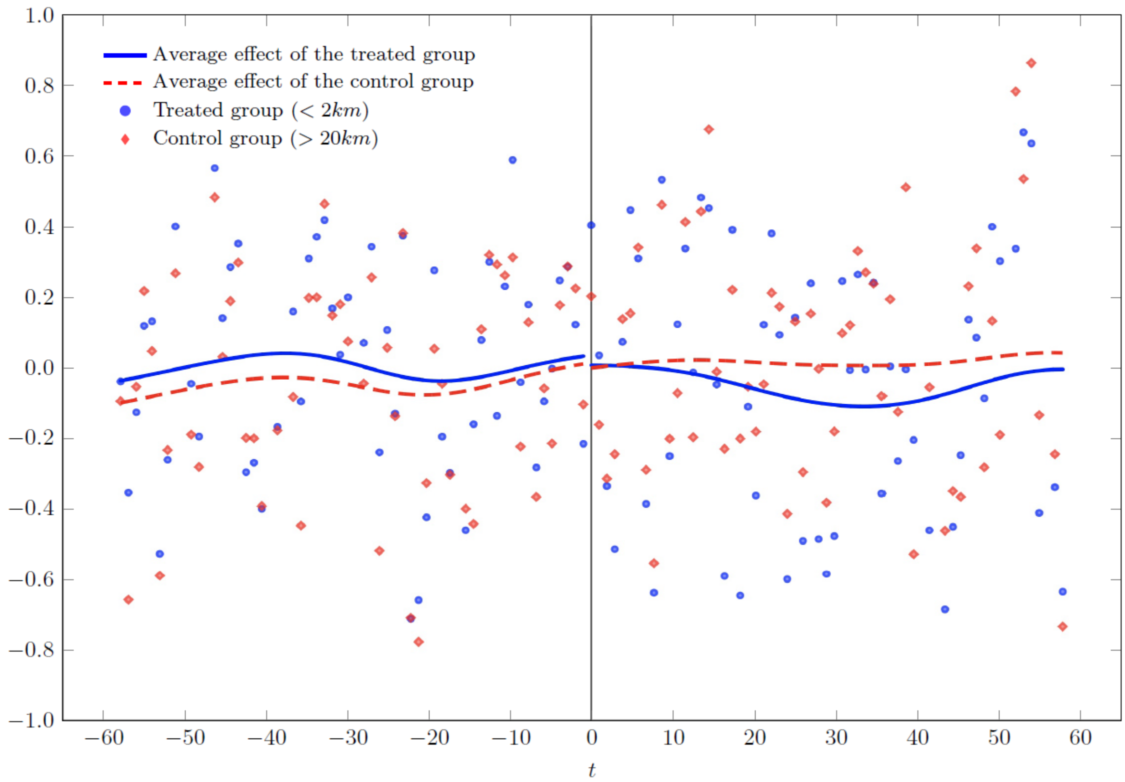
Appendix: Figures and tables

Figure A1: Air quality monitors and subway stations



Source: www.bjstats.gov.cn/xwgb/tjgb/ndgb/201402/t20140213_267744.htm

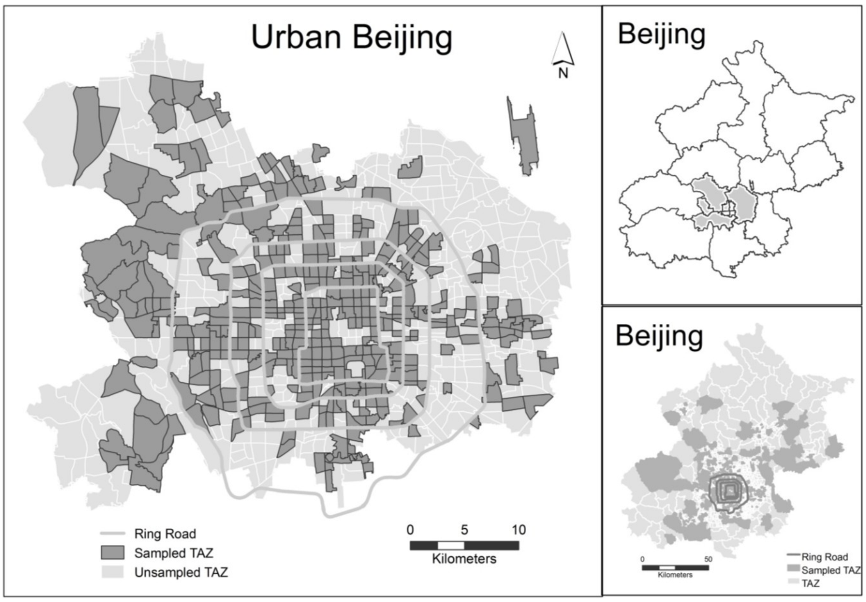
Figure A2: Residualized ln(Air P ollution) for 60 days before and after the opening



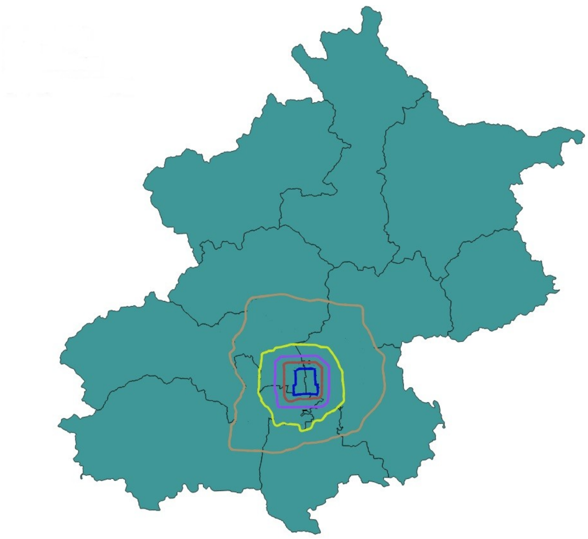
Note: Residualized plots of ln(Air P ollution) after controlling for weather conditions, monitor fixed effects, time fixed effects: year, season, day of week and holiday, and monitor-specific time trends.

Figure A3: Transportation regions considered in study of effects on travel mode, housing prices, and welfare

(a) Traffic Analysis Zones in Beijing

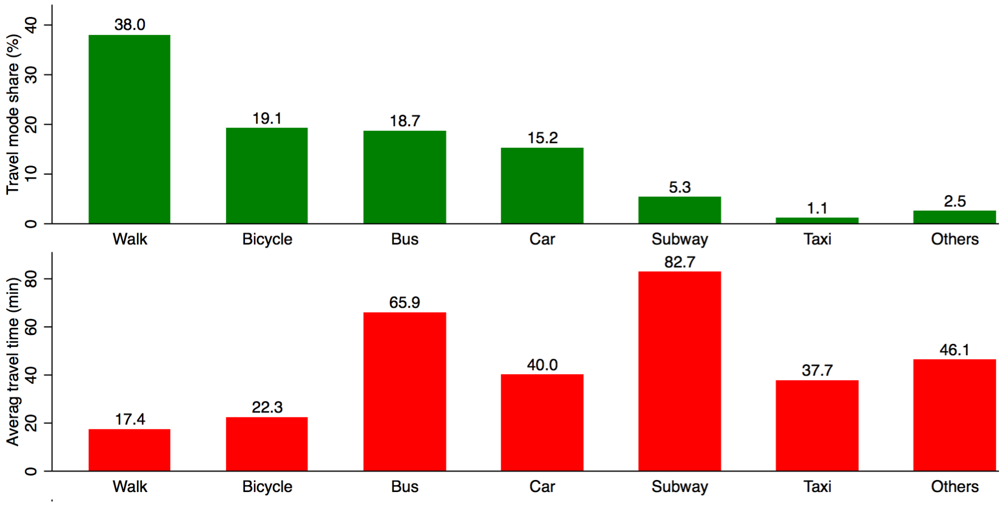


(b) District-Ring Road Intersections



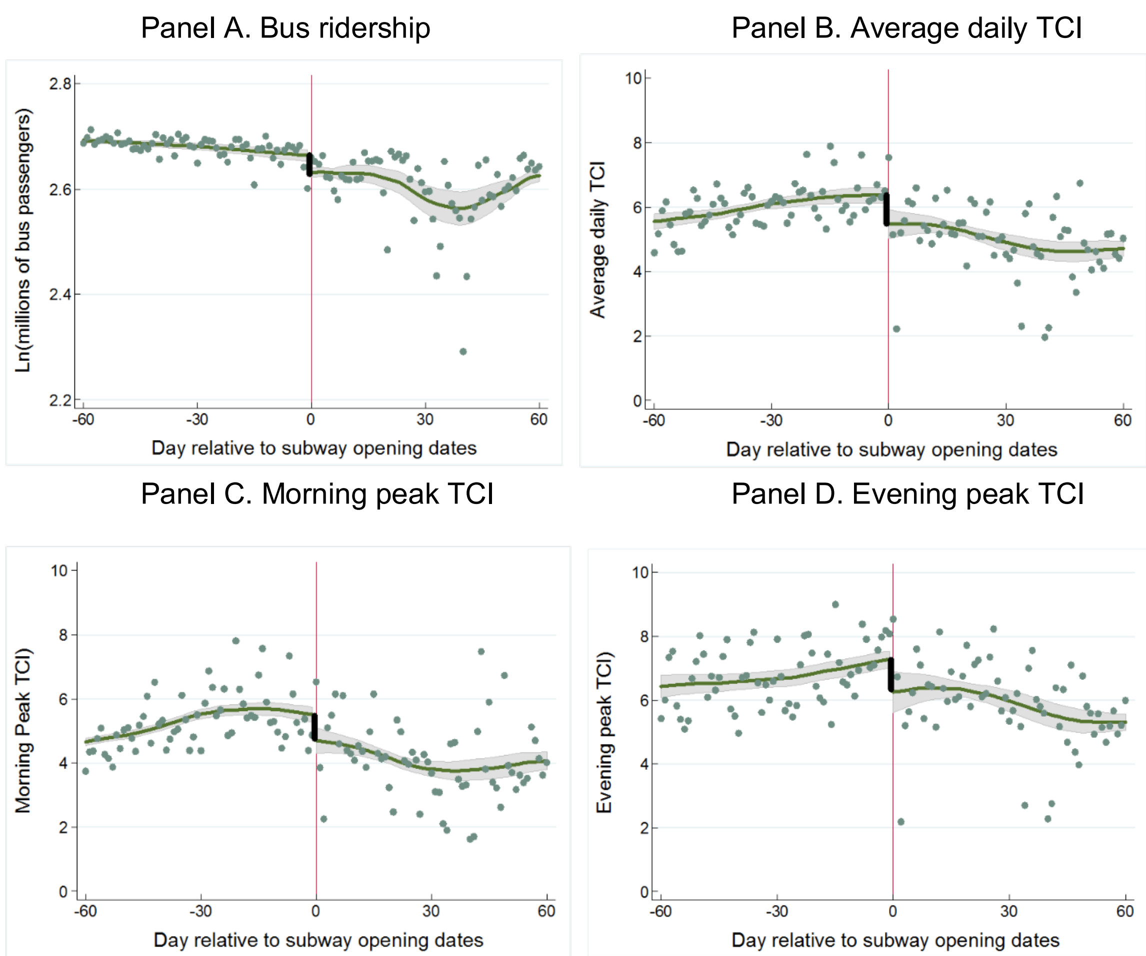
Note: Panel (a) of the figure displays the sampling of the 2010 Beijing Household Travel Survey. Each of the small polygons corresponds to a Traffic Analysis Zone, where the sampled TAZs are located predominantly within the central, more populated parts of Beijing– specifically within the 6th ring road. Panel (b) shows the regions used to calculate travel times and distances for the housing data, which are polygons formed by the intersection of the ring roads with district boundaries. The maps are constructed by authors.

Figure A4: Trip share, time and cost by mode



Note: This figure shows summary statistics for data from the 2010 Beijing Household Travel Survey. The first bar chart displays the share of trips taken by each mode type. The second chart shows the average travel time for each travel mode.

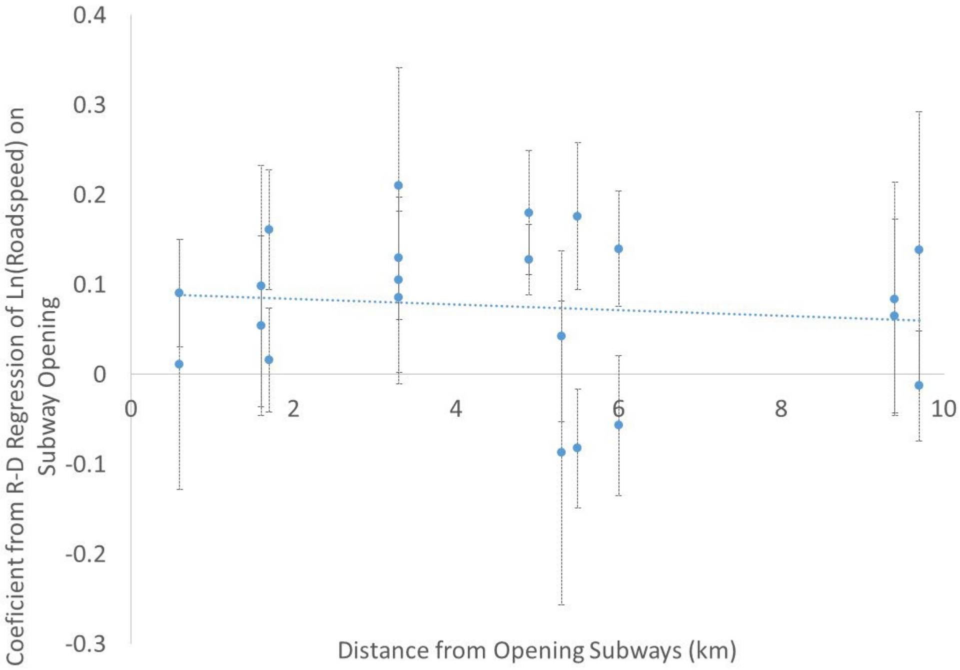
Figure A5: Outcome variables around subway opening dates



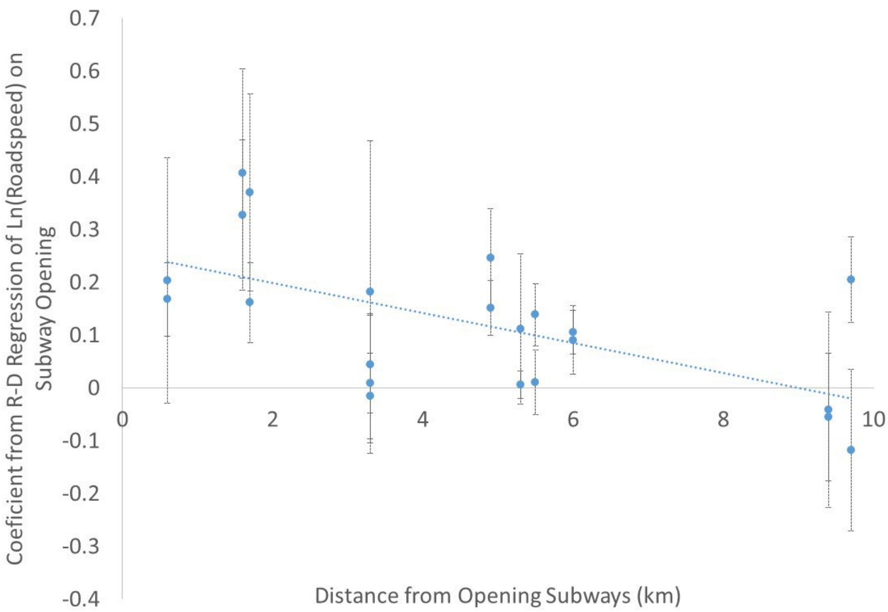
Note: Each dot represents the average of the indicated variable across the five subway openings studied here. The trendline in each graph represents a 3rd order polynomial. Shaded areas represent 95% confidence intervals for the trendline. Weekends and holidays are dropped before taking averages for these graphs.

Figure A6: R-D Regressions of roadspeed on subway openings

Panel A. Morning Roadspeed

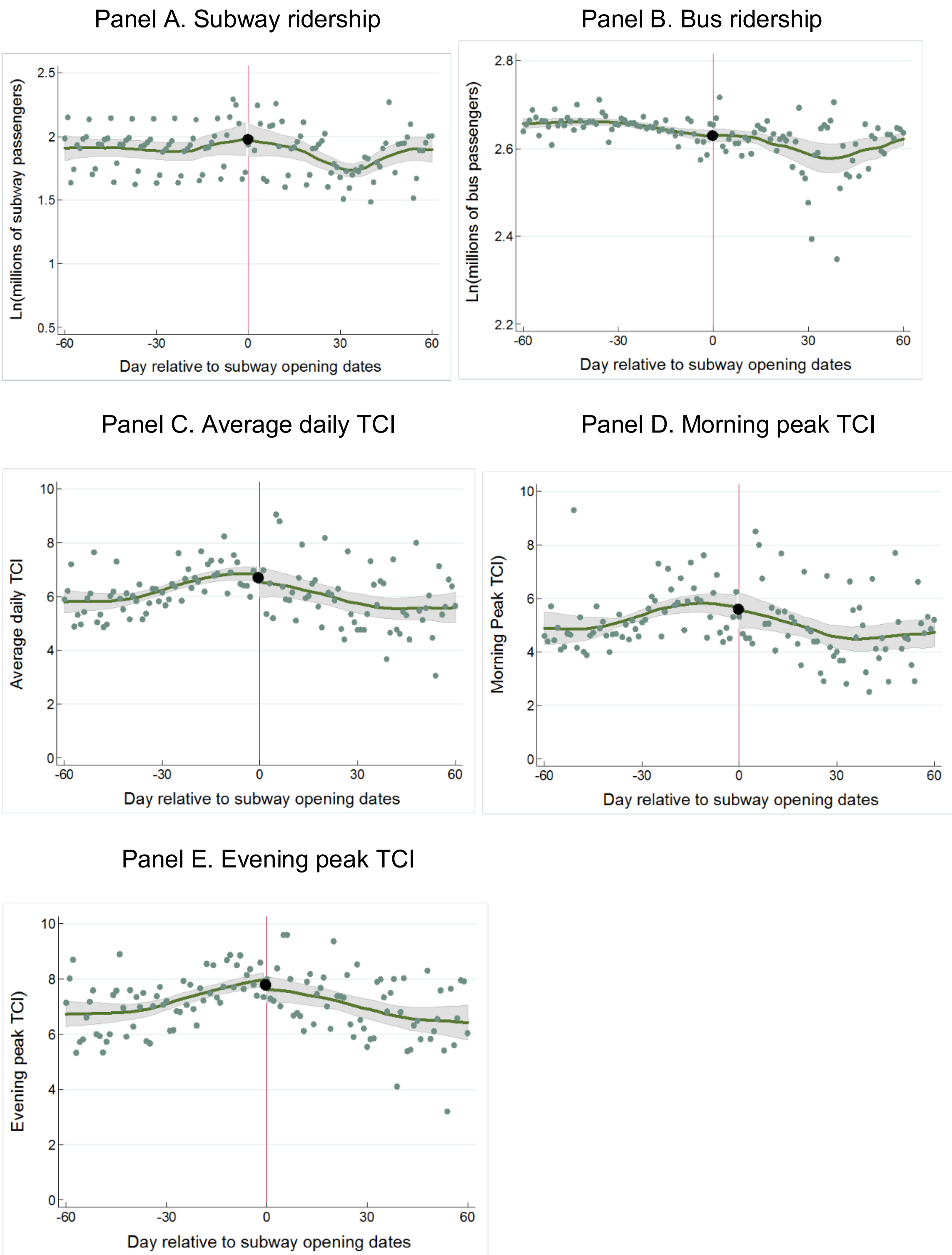


Panel B. Evening Roadspeed



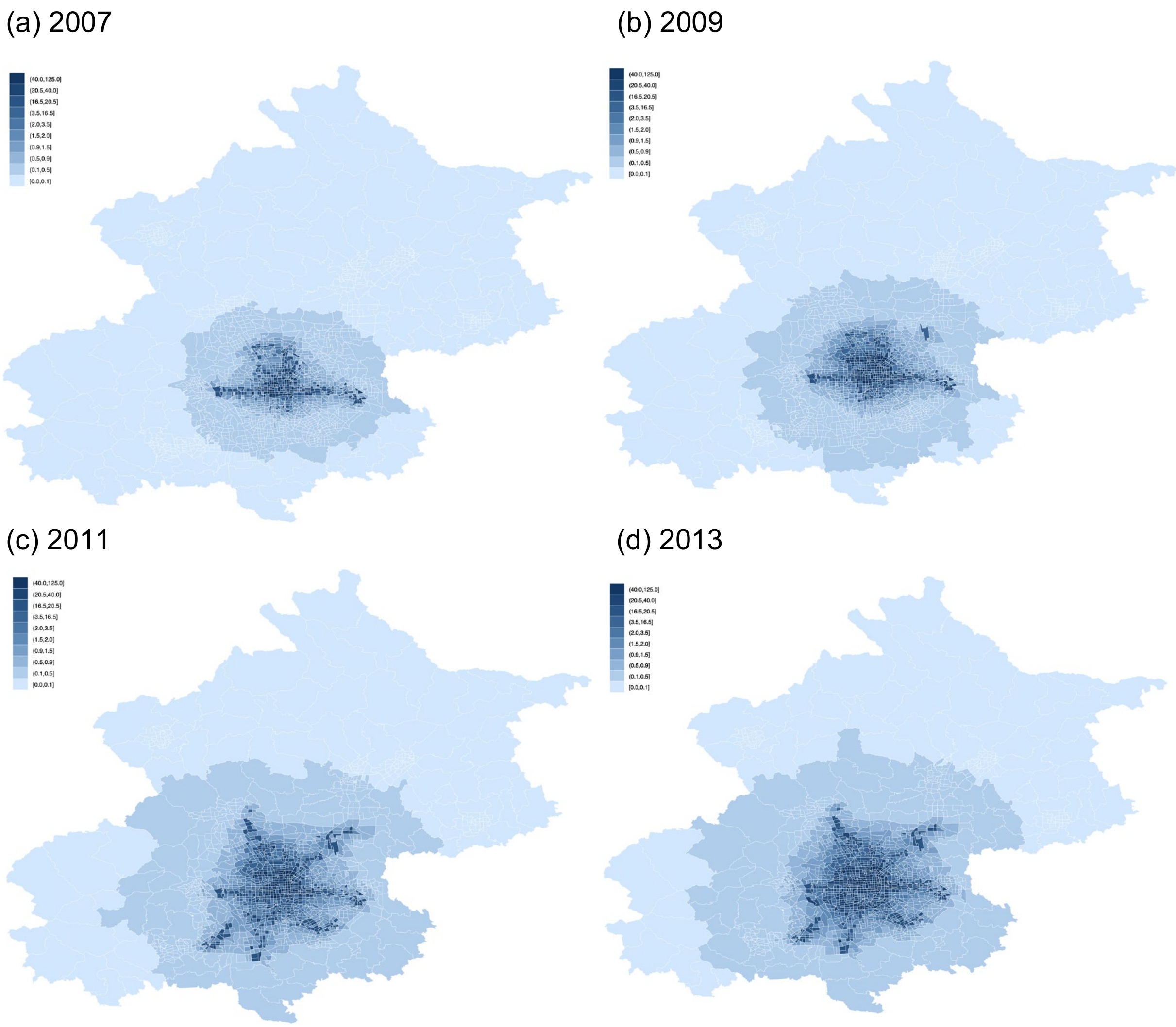
Note: Each dot represents the result of regressions of equation (1), where the dependent variable is the natural logarithm of average road speed of a road segment during morning rush hour or evening rush hour. Covariates in these regressions are the same as in specification 4 from table 1.4. The standard error of each regression is indicated by the error bar.

Figure A7: Outcome variables during placebo comparison periods



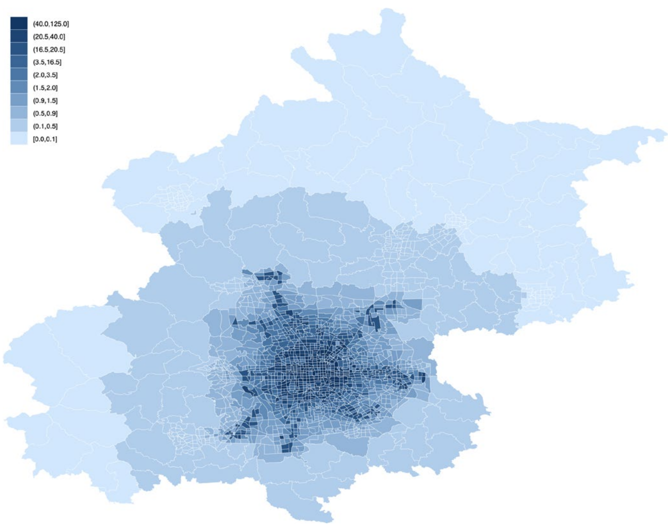
Note: Each dot represents the average of the indicated variable across the four subway openings studied here. The trendline in each graph represents a 3rd order polynomial. Shaded areas represent 95% confidence intervals for the trendline. Weekends and holidays are dropped before taking averages for these graphs.

Figure A8: Subway expansion and network density at the TAZ level



Note: The maps are constructed by authors.

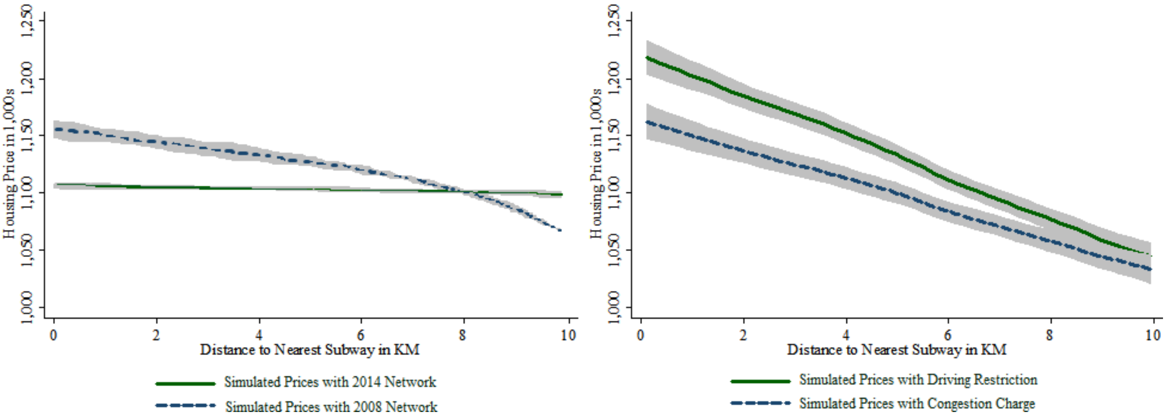
Figure A9: Beijing subway network density at the TAZ level as of 2016



Note: The map is constructed by authors.

Figure A10: Simulated price gradients: distance to subway

(a) No Policy & Subway Expansion (b) Driving Restriction & Congestion Charge



Note: This figure shows simulated price gradients based on equilibrium prices for which predicted demand from the model equate to the supply of houses. The horizontal axis reports the distance to the nearest subway station from each house in kilometers. The dashed line is based on the 2008 subway network and the solid line is the 2014 subway network. Panel (a) reports the effect with only a subway expansion, where we have simulated behavior as if there had been no driving restriction. Panel (b) reports simulated prices with the driving restriction and congestion charge in place.

Table A1: Sample subway lines and selection of sample period for effects on traffic congestion

Subway Opening	Subway Lines	Opening Date	Sample Period	Stations	Length (km)	Cost (billions of RMB)	Avg. Daily Ridership (millions)
1	Line 4	9/28/2009	7/30/09 – 11/27/09	24	28.2	15.8	0.527
2	Lines 15, CP, DX, FS, YZ	12/30/2010	10/31/10 – 2/28/11	54	122.4	47.2	0.155
3	Lines 8, 9	12/31/2011	11/1/11 – 2/29/12	13	16.5	19.3	0.105
4	Line 6	12/30/2012	10/31/12 – 2/28/13	20	30.4	28.0	0.340
5	Line 14W	5/5/2013	3/6/13 – 7/4/13	7	12.4	3.6	0.041
6	Lines 7, 14E	12/28/2014	10/29/14 – 2/26/15	19	23.7	29.4	0.263

Note: The sample period of the main specification is 60 days before and after the date of the opening.

Table A2: Traffic congestion index (TCI) definitions

TCI	Description	Travel Time
0 - 2	Smooth	1 minute
2 - 4	Basically smooth	1.3 – 1.5 minutes
4 - 6	Slightly congested	1.5 – 1.8 minutes
6 - 8	Moderately congested	1.8 – 2.0 minutes
8 - 10	Seriously congested	>2.1 minutes

Note: Travel time corresponds to the amount of time to travel a given distance. This time varies, depending on the speed of the measured road in uncongested circumstances.

Table A3: Summary statistics for effects on traffic congestion

Variable	Full Sample	Before Openings	After Openings	Difference
Includes Holidays and Weekends (N = 726)				
Newly Opened Subway lines (millions of riders)	0.120	0	0.239	0.239***
	[0.006]	[0]	[0.009]	[0.009]
Existing Subway Lines (millions of riders)	6.430	6.727	6.138	-0.589***
	[0.079]	[0.109]	[0.112]	[0.156]
Bus Passenger Volume (millions of riders)	13.032	13.829	12.248	-1.581***
	[0.071]	[0.056]	[0.115]	[0.129]
Traffic Congestion Index (TCI, Daily Average)	4.593	5.156	4.040	-1.116***
	[0.070]	[0.090]	[0.099]	[0.134]
Traffic Congestion Index (TCI, Morning Peak)	3.629	4.089	3.177	-0.912***
	[0.084]	[0.109]	[0.103]	[0.150]
Traffic Congestion Index (TCI, Evening Peak)	5.518	6.195	4.853	-1.342***
	[0.081]	[0.999]	[0.117]	[0.154]
Holiday (0,1)	0.101	0.039	0.161	0.122***
	[0.012]	[0.011]	[0.021]	[0.024]
Extreme Weather (0,1)	0.044	0.044	0.044	-0.001
	[0.008]	[0.019]	[0.011]	[0.015]
Percentage of cars not banned (0, 100)	80.0	80.0	79.9	-0.100
	[0.150]	[0.207]	[0.207]	[0.300]
Excludes Holidays and Weekends (N = 475)				
Newly Opened Subway lines (millions of riders)	0.117	0	0.254	0.254***
	[0.008]	[0]	[0.011]	[0.011]
Existing Subway Lines (millions of riders)	6.663	7.138	6.963	-0.176
	[0.092]	[0.129]	[0.130]	[0.184]
Bus Passenger Volume (millions of riders)	13.403	14.373	13.248	-1.125***
	[0.064]	[0.039]	[0.093]	[0.098]
Traffic Congestion Index (TCI, Daily Average)	4.978	6.001	5.002	-0.999***
	[0.079]	[0.070]	[0.096]	[0.117]
Traffic Congestion Index (TCI, Morning Peak)	4.202	5.223	4.221	-1.003***
	[0.099]	[0.077]	[0.105]	[0.129]
Traffic Congestion Index (TCI, Evening Peak)	5.699	6.789	5.759	-1.031***
	[0.087]	[0.099]	[0.124]	[0.157]
Extreme Weather (0,1)	0.048	0.053	0.044	-0.009
	[0.010]	[0.014]	[0.014]	[0.020]
Percentage of cars not banned (0, 100)	80.0	80.0	79.9	-0.100
	[0.150]	[0.207]	[0.207]	[0.300]

Note: These summary statistics report average transportation usage levels 60 days before and after the 6 subway stations openings. Other variables in our research include dummies for weekdays and subway lines, respectively. For brevity, they are not reported here. Extreme weather includes *heat waves, cold spells, rainstorms, and gale and snow*, based on meteorological definitions at Baidu Encyclopedia (http://baike.baidu.com/).

Table A4: Variable descriptions for effects on air quality

Variable	Definition
(a) Air Pollution Indicators, monitoring station (i) × daily (t)	
API_{it}	Air Pollution Index ranging from 0 to 500. This index measured between 2008 and 2012 and it accounts for sulfur dioxide (SO_2), nitrogen dioxide (NO_2), suspended particulates (PM_{10}).
AQI_{it}	Air Quality Index ranging from 0 to 500. This index has been measured since 2013 and it accounts for SO_2, NO_2, PM_{10}, $PM_{2.5}$ and O_3.
(b) Subway Density Measures, monitoring station (i) × daily (t)	
$Density_{it}$	Subway network density centered at monitoring station i, which is defined as the total number of stations at time t weighted by the inverse of squared distances from monitoring station i to each subway stations in Beijing.
$\widetilde{Density}_{it}$	Subway network density centered at monitoring station i, which is defined as the total number of stations at time t weighted by both the daily ridership of each subway line and the inverse of squared distances from monitoring station i to each subway stations in Beijing.
$Treated_{it}$	Treated group or treated air pollution monitoring station. 1 if it is treated, 0 otherwise. Air pollution monitoring station i is treated when there is at least one new subway station (j) opened within 2km distance and we keep it as treated for 60 days after the opening, defined as $\mathbf{1}(Post_t) \times \mathbf{1}(Distance_{ij} \leq 2km, j \in N_\tau)$.
$N_{it} \times Treated_{it}$	Heterogeneity of treated group or treated air pollution monitoring station, which counts total number of new subway stations opened within 2km distance and kept as treated for 60 days after the opening, defined as $N_{it} = \mathbf{1}(Post_t) \times \sum_{j \in N_t} \mathbf{1}(Distance_{ij} \leq 2km)$.
(c) Weather Variables, daily (t)	
Air temperature (^oC)	Average daily temperature.
Relative humidity (%)	Average daily relative humidity.
Precipitation (mm)	Total daily rainfall or snowmelt.
Wind speed (km/h)	Average daily wind speed.
Wind direction (cat.)	The vector summation of hourly wind direction with its speed as the the length of each vector.
Rain/Snow/Storm/Fog	Rain/Snow/Storm/Fog dummy: 1 if there was rain/snow/storm/fog , 0 otherwise.

Table A5: Conversion from pollutants concentration to API and AQI

Air Pollution Index (API)		Pollutants					
value	level	PM_{10} ($\mu g/m^3$)	PM2.5 ($\mu g/m^3$)	O_3 ($\mu g/m^3$)	CO (mg/m^3)	NO_2 ($\mu g/m^3$)	SO_2 ($\mu g/m^3$)
0-50	Excellent	0-50				0-80	0-50
50-100	Good	50-150				80-120	50-150
100-200	Slightly polluted	150-350				120-280	150-800
200-300	Moderately polluted	350-420				280-565	800-1600
300-400	Severely polluted	420-500				565-750	1600-2100
400-500	Severely polluted	500-600				750-940	2100-2620

Air Quality Index (AQI)		Pollutants					
value	level	PM_{10} ($\mu g/m^3$)	PM2.5 ($\mu g/m^3$)	O_3 ($\mu g/m^3$)	CO (mg/m^3)	NO_2 ($\mu g/m^3$)	SO_2 ($\mu g/m^3$)
0-50	Good	0-50	0-35	0-100	0-2	0-40	0-50
50-100	Moderate	50-150	35-75	100-160	2-4	40-80	50-150
101-150	Unhealthy for SG	150-250	75-115	160-215	4-14	80-180	150-475
151-200	Unhealthy	250-350	115-150	215-265	14-24	180-280	475-800
201-300	Very unhealthy	350-420	150-250	265-800	24-36	280-565	800-1600
>300	Hazardous	>420	>250	>800	>36	>565	2100-2620

Note: During 2008-2012, the Chinese government adopts the Air Pollution Index (API) which takes into account three pollutants. Starting from 2013, the Chinese government replaces API with Air Quality Index (AQI) which considers PM2.5 separately from PM10 as a major pollutant, and also Ozone.

Table A6: Summary statistics for effects on air quality

Main variables	Mean	S.D.	Min	Max	N
(a) Air Pollution					
API_{it}	82.84	48.56	5.00	500.00	49103
AQI_{it}	124.64	80.02	8.00	500.00	54939
(b) Subway Density					
$Density_{it}$ (non-weighted)	2.48	3.58	0.01	16.26	297
$\widetilde{Density}_{it}$ (ridership-weighted)	0.19	0.30	0.00	1.34	297
$N_{it} \times Treated_{it}$	0.16	0.69	0.00	6.00	297
(c) Weather variables					
Air temperature (^oC)	12.97	11.39	-15.04	33.05	3533
Wind speed (*m/s*)	1.97	1.58	0.02	10.21	3533
Precipitation (*mm*)	1.97	8.82	0.00	262.64	3339
Relative humidity (%)	54.64	20.20	6.97	97.83	3533
Wind direction (*cat.*)	7.95	4.94	1.00	16.00	3533

Note: The air quality panel summarizes the daily Air Pollution Index from 2008-2012 and Air Quality Index since 2013 from 27 air quality monitors in Beijing. The density panel summarizes the daily subway density measures at monitoring station level. The weather panel summarizes the daily, city-level weather conditions.

Table A7: Changes in air pollution before and after openings

	ln(Air Pollution)			
	Before	After	Diff.	Diff-in-Diff.
Control	4.428	4.437	0.009	
	(0.008)	(0.008)	(0.011)	
Treated	4.483	4.535	0.052	0.043
	(0.018)	(0.022)	(0.028)	(0.031)
	Residualized ln(Air Pollution)			
	Before	After	Diff.	Diff-in-Diff.
Control	0.005	-0.004	-0.009	
	(0.005)	(0.005)	(0.007)	
Treated	0.022	-0.033	-0.055	-0.046
	(0.014)	(0.015)	(0.021)	(0.022)

Note: The top panel shows the sample mean of ln(Air P ollution) 60 days before and after each subway line opens. The bottom panel shows the sample means of residualized ln(Air P ollution) after after controlling for weather conditions, monitor fixed effects, time fixed effects: year, season, day of week and holiday, and monitor-specific time trends. The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The standard errors are in parentheses.

Table A8: Beijing subway expansion and network density

Opening	Subway		N. of Stations		Standardized Density	
date	line	length	new	total	non-weighted	ridership-weighted
(τ)	(ℓ)	(km)	(N_τ)	($\mathcal{N}_\tau$)	($Density_\tau/\sigma$)	($\widetilde{Density}_\tau/\tilde{\sigma}$)
Before 2008	1, 2, 5, 13, BT	140	93	93	0.27	0.27
July 19, 2008	8, 10, AE	57	30	123	0.39	0.44
Sep 28, 2009	4	28	24	147	0.45	0.52
Dec 30, 2010	15, DX, CP, FS, YZ	108	49	196	0.57	0.54
Dec 31, 2011	9	36	19	215	0.62	0.56
Dec 30, 2012	6	70	46	261	0.80	0.75
May 5, 2013	14 (West)	14	9	270	0.82	0.76
Dec 28, 2013	8 (Extension)	7	7	277	0.84	0.77
Dec 28, 2014	7	62	42	319	0.93	0.81
Dec 26, 2015	14 (East)	11	15	334	0.94	0.82
Dec 31, 2016	16	20	11	345	0.96	0.82

Note: The names of suburban subway lines are shown as abbreviation: Airport Express (AE), Batong (BT), Daxing (DX), Changping (CP), Fangshan (FS) and Yizhuang (YZ). There were 93 subway stations operating before our data period. Network density centered at an air pollution monitoring station is defined as the weighted sum of subway weighted by the squared inverse distance from the monitoring station to each subway station operating in the network as of the opening date. It is standardized by dividing its standard deviation. The ridership-weighted density is the reweight of the density by ridership of subway line. Standard deviations of the both densities are σ = 3.58 and σ = 29.77 respectively. All density measures are averaged across monitoring stations for each opening date.

Table A9: Parellel trend test for effects on air quality

	Dependent variable: $\ln(Air\ Pollution_{it})$			
	(1)	(2)	(3)	(4)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau - 60 \leq t < \tau - 50)$	-0.080	-0.099	-0.067	-0.076
	(0.061)	(0.061)	(0.062)	(0.083)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau - 50 \leq t < \tau - 40)$	-0.147***	-0.158***	-0.147***	-0.157***
	(0.043)	(0.044)	(0.045)	(0.056)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau - 40 \leq t < \tau - 30)$	-0.010	-0.022	-0.022	-0.034
	(0.049)	(0.051)	(0.052)	(0.058)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau - 30 \leq t < \tau - 20)$	-0.065	-0.076	-0.088*	-0.095
	(0.050)	(0.050)	(0.052)	(0.060)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau - 20 \leq t < \tau - 10)$	-0.029	-0.044	-0.063	-0.064
	(0.045)	(0.047)	(0.047)	(0.054)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau \leq t < \tau + 10)$	-0.090*	-0.102**	-0.062	-0.054
	(0.048)	(0.049)	(0.045)	(0.056)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau + 10 \leq t < \tau + 20)$	0.016	0.000	0.041	0.034
	(0.053)	(0.053)	(0.051)	(0.061)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau + 20 \leq t < \tau + 30)$	-0.178***	-0.190***	-0.178***	-0.176***
	(0.052)	(0.052)	(0.052)	(0.062)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau + 30 \leq t < \tau + 40)$	-0.256***	-0.267***	-0.277***	-0.274***
	(0.053)	(0.053)	(0.054)	(0.063)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau + 40 \leq t < \tau + 50)$	-0.172***	-0.185***	-0.225***	-0.227***
	(0.057)	(0.057)	(0.056)	(0.064)
$\mathbf{1}(Distance_{ij} \leq 2km) \times \mathbf{1}(\tau + 50 \leq t < \tau + 60)$	-0.044	-0.054	-0.112**	-0.116*
	(0.051)	(0.051)	(0.053)	(0.063)
Time Window (days)	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$
Weather Controls	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Monitor FE	Y	Y	Y	Y
Monitor FE×Driving	N	Y	Y	Y
Monitor FE×Trend	N	N	Y	Y
Staggered Rollout	N	N	N	Y
N	17231	17231	17231	17231
R^2	0.53	0.53	0.54	0.56

Note: Each column reports results from an OLS regression where the dependent variable is ln(Air P ollution) and the key explanatory variables are the treatment dummies (the interaction of each 10 days within the 60-day time window around the opening dates and there is a new subway station within 2km from the monitoring station). The control group is the monitors outside 20km. The unit of observation is monitor-day. Column (4) relies on the staggered rollout. The weather controls include daily variables: temperature (C_0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed , dummies for rain, snow, storm, fog. The time fixed effects include year, season, day-of-week, holiday-of-sample dummies. Parentheses contain standard errors clustered at the day level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

Table A10: Summary statistics of Beijing Household Travel Survey data

Panel A: Travel Survey				
Variable	Mean	SD	Min	Max
Household size	2.47	0.98	1	5
Income (RMB ’000)	64.49	30.21	50	300
# of workers	1.18	0.92	0	4
House size (*m*2)	75.85	49.61	5	3,800
House owner (=1)	0.69	0.46	0	1
Having a car (=1)	0.29	0.45	0	1
# of cars	0.31	0.51	0	3
# of bikes	0.96	0.93	0	5
# of ebikes	0.15	0.40	0	4
# of motorcycles	0.03	0.18	0	3
Panel B: Mortgage Data				
Year	2010	2	2008	2014
Household Income (1,000s 2010 RMB)	153.7	81.0	15.1	717.1
Borrower Age	33.0	5.6	23	55
Real House Sale Price (1,000s 2010 RMB)	957.7	0.0	193.9	3,303.2
Unit Size (square meters)	85.8	30.5	36.4	199.6
Distance to Work (km)	10.5	7.4	0.1	53.3
Distance to Subway from Home (km)	5.24	8.78	0.26	51.99

Note: Panel A of the table reports summary statistics for 12,105 home-to-work or work-to-home trips in the travel survey data. Panel B reports summary statistics for the 13,865 homes that are used to construct the mortgage data sample.

Table A11: Summary statistics of the mortgate data

Panel A: Travel Survey				
Variable	Mean	SD	Min	Max
Household size	2.47	0.98	1	5
Income (RMB ’000)	64.49	30.21	50	300
# of workers	1.18	0.92	0	4
House size (*m*2)	75.85	49.61	5	3,800
House owner (=1)	0.69	0.46	0	1
Having a car (=1)	0.29	0.45	0	1
# of cars	0.31	0.51	0	3
# of bikes	0.96	0.93	0	5
# of ebikes	0.15	0.40	0	4
# of motorcycles	0.03	0.18	0	3
Panel B: Mortgage Data				
Year	2010	2	2008	2014
Household Income (1,000s 2010 RMB)	153.7	81.0	15.1	717.1
Borrower Age	33.0	5.6	23	55
Real House Sale Price (1,000s 2010 RMB)	957.7	0.0	193.9	3,303.2
Unit Size (square meters)	85.8	30.5	36.4	199.6
Distance to Work (km)	10.5	7.4	0.1	53.3
Distance to Subway from Home (km)	5.24	8.78	0.26	51.99

Note: Panel A of the table reports summary statistics for 12,105 home-to-work or work-to-home trips in the travel survey data. Panel B reports summary statistics for the 13,865 homes that are used to construct the mortgage data sample.

Table A12: R-D results – extended sample period without openings 4 and 5

Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
30 Days Around Opening (N = 157)						
Subway Open	0.084***	-0.014	-0.025**	-0.502	-0.320	-0.685
	[0.023]	[0.025]	[0.008]	[0.502]	[0.514]	[0.665]
R^2	0.974	0.981	0.862	0.576	0.728	0.515
60 Days Around Opening (N = 317)						
Subway Open	0.138***	0.030	-0.019	-0.721*	-1.240**	-0.207
	[0.015]	[0.019]	[0.013]	[0.349]	[0.445]	[0.345]
R^2	0.826	0.939	0.720	0.598	0.565	0.504
90 Days Around Opening (N = 473)						
Subway Open	0.067***	-0.047**	0.030	-1.082***	-1.569***	-0.597***
	[0.020]	[0.016]	[0.068]	[0.137]	[0.224]	[0.133]
R^2	0.860	0.942	0.120	0.514	0.460	0.461
120 Days Around Opening (N = 630)						
Subway Open	0.050***	-0.092***	-0.068**	-0.982***	-1.249***	-0.718***
	[0.017]	[0.016]	[0.031]	[0.132]	[0.199]	[0.122]
R^2	0.845	0.948	0.085	0.463	0.412	0.450
150 Days Around Opening (N = 791)						
Subway Open	0.085***	-0.063***	-0.074***	-0.828***	-1.177***	-0.482***
	[0.013]	[0.011]	[0.013]	[0.133]	[0.185]	[0.146]
R^2	0.823	0.941	0.099	0.367	0.382	0.373
180 Days Around Opening (N = 941)						
Subway Open	0.080***	-0.059***	-0.094***	-0.906***	-1.329***	-0.487***
	[0.015]	[0.008]	[0.012]	[0.137]	[0.189]	[0.157]
R^2	0.814	0.948	0.105	0.371	0.375	0.372

Note: This table reports results of regressions of specification 4 from table 1. All regressions include a third-order polynomial in the predictor. Holidays and weekends are excluded from these models. Regressions with “covariates” contain weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Regression discontinuity-based results – alternative specifications checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
Excluding Days around Holidays (All subway openings)						
Subway Open	0.133***	0.041***	-0.025***	-0.722***	-1.242***	-0.218
(N = 420)	[0.010]	[0.003]	[0.006]	[0.153]	[0.275]	[0.149]
R^2	0.974	0.988	0.799	0.670	0.601	0.562
No Coinciding Travel Policies (Drops Openings 2 and 5)						
Subway Open	0.135***	0.033*	-0.017	-0.664*	-1.122**	-0.211
(N = 316)	[0.016]	[0.018]	[0.010]	[0.337]	[0.403]	[0.357]
R^2	0.840	0.939	0.732	0.641	0.598	0.535
Excludes Opening 1						
Subway Open	0.043	0.011	-0.030*	-0.498	-0.513	-0.493*
(N = 394)	[0.025]	[0.022]	[0.015]	[0.286]	[0.344]	[0.268]
R^2	0.616	0.764	0.600	0.668	0.612	0.618
Excludes Opening 2						
Subway Open	0.129***	0.030	-0.018*	-0.659*	-1.083**	-0.239
(N = 395)	[0.015]	[0.017]	[0.009]	[0.321]	[0.384]	[0.334]
R^2	0.847	0.941	0.718	0.614	0.582	0.516
Excludes Opening 3						
Subway Open	0.131***	0.036*	-0.016*	-0.722**	-1.113***	-0.339
(N = 395)	[0.015]	[0.017]	[0.007]	[0.316]	[0.358]	[0.316]
R^2	0.838	0.932	0.704	0.581	0.573	0.482
Excludes Opening 4						
Subway Open	0.130***	0.026	-0.020	-0.718*	-1.193**	-0.246
(N = 396)	[0.013]	[0.018]	[0.012]	[0.327]	[0.422]	[0.315]
R^2	0.837	0.943	0.707	0.555	0.542	0.471
Excludes Opening 5						
Subway Open	0.122***	0.031*	-0.022**	-0.733**	-1.155***	-0.320
(N = 396)	[0.014]	[0.016]	[0.010]	[0.315]	[0.378]	[0.313]
R^2	0.823	0.924	0.680	0.602	0.576	0.502
Excludes Opening 6						
Subway Open	0.135***	0.031**	-0.031***	-0.946**	-1.497***	-0.405
(N = 399)	[0.020]	[0.014]	[0.005]	[0.323]	[0.360]	[0.366]
R^2	0.884	0.917	0.518	0.576	0.561	0.467
Includes Week FE						
Subway Open	0.075**	-0.025	-0.039***	-1.207**	-1.084**	-1.333*
(N = 475)	[0.035]	[0.023]	[0.010]	[0.530]	[0.479]	[0.678]
R^2	0.866	0.944	0.763	0.704	0.715	0.636

Note: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). The reported coefficient in each cell is the coefficient on “Subway Open,” a dummy variable indicating whether the new subway line had opened. All regressions are based on model specification 4 of table 1, and include a third order polynomial. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: R-D results – sample window tests

Dependent Variable	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
30 Days Around Opening (N = 236)						
Subway Open	0.073***	-0.008	-0.028***	-0.733	-0.445	-1.034*
	[0.018]	[0.019]	[0.006]	[0.432]	[0.464]	[0.525]
R^2	0.969	0.982	0.837	0.512	0.654	0.464
45 Days Around Opening (N = 355)						
Subway Open	0.130***	0.045*	0.004	-0.646*	-0.723	-0.578
	[0.021]	[0.023]	[0.011]	[0.354]	[0.413]	[0.453]
R^2	0.920	0.942	0.749	0.531	0.580	0.434
60 Days Around Opening (N = 475)						
Subway Open	0.117***	0.028*	-0.023**	-0.728***	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485

Note: This table reports results of regressions of specification 4 from table 1. All regressions include a third-order polynomial in the predictor. Holidays and weekends are excluded from these models. Regressions with "covariates" contain weekday dummies, dummies for which license plates are excluded from Beijing roads that day, extreme weather dummies, and dummies for subway line. All standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Regression discontinuity robustness check – other order polynomials

	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
1st order polynomial						
Subway Open	0.102***	0.018	-0.029***	-0.799**	-1.169***	-0.437
	[0.014]	[0.017]	[0.010]	[0.301]	[0.360]	[0.296]
R^2	0.792	0.911	0.594	0.427	0.509	0.318
2nd order polynomial						
Subway Open	0.116***	0.024	-0.023**	-0.696**	-1.100***	-0.300
	[0.013]	[0.017]	[0.009]	[0.289]	[0.354]	[0.279]
R^2	0.828	0.918	0.668	0.535	0.548	0.436
3rd order polynomial (Baseline)						
Subway Open	0.117***	0.028*	-0.023**	-0.728**	-1.120***	-0.343
	[0.013]	[0.016]	[0.009]	[0.302]	[0.362]	[0.295]
R^2	0.830	0.927	0.668	0.578	0.562	0.485
5th order polynomial						
Subway Open	0.113***	0.023	-0.025***	-0.734**	-1.112***	-0.364
	[0.014]	[0.015]	[0.007]	[0.305]	[0.360]	[0.307]
R^2	0.840	0.932	0.686	0.625	0.593	0.522
7th order polynomial						
Subway Open	0.091***	0.011	-0.029***	-0.888***	-1.120***	-0.665**
	[0.011]	[0.012]	[0.004]	[0.295]	[0.350]	[0.306]
R^2	0.846	0.934	0.719	0.652	0.625	0.562
9th order polynomial						
Subway Open	0.091***	0.011	-0.029***	-0.885***	-1.124***	-0.656*
	[0.011]	[0.012]	[0.004]	[0.297]	[0.350]	[0.307]

	Ln(All SPV)	Ln(Existing SPV)	Ln(BPV)	TCI (all)	TCI (morning)	TCI (evening)
R^2	0.847	0.934	0.719	0.653	0.625	0.565
11th order polynomial						
Subway Open	0.089***	0.012	-0.034***	-0.817**	-0.983**	-0.663*
	[0.013]	[0.012]	[0.005]	[0.291]	[0.334]	[0.313]
R^2	0.847	0.934	0.721	0.654	0.630	0.565

Note: This table reports results of regressions of equation (1) when the dependent variable is bus passenger volume (BPV), subway passenger volume (SPV), or the traffic congestion index (TCI). The reported coefficient in each cell is the coefficient on “Subway Open,” a dummy variable indicating whether the new subway line had opened. All specifications are similar to that of specification 4 of table 1. Standard errors are clustered using a dummy for the interaction of the weekday and which license plates are excluded that day.

Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A16: OLS: The impact of subway network density on air pollution

	Dependent variable: ln(Air Pollution$_{it}$)			
	(1)	(2)	(3)	(4)
Densityit	0.049***	-0.006***	-0.007***	-0.015***
	(0.001)	(0.002)	(0.002)	(0.003)
Temperature (C)	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Relative humidity (%)	0.009***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Rainfall/snow(mm)	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Wind speed (m/s)	-0.071**	-0.071**	-0.072**	-0.071**
	(0.031)	(0.031)	(0.031)	(0.031)
Constant	4.027***	4.085***	4.086***	4.057***
	(0.073)	(0.074)	(0.079)	(0.080)
Monitor FE	N	Y	Y	Y
Monitor FE Driving	N	N	Y	Y
Monitor FE Trend	N	N	N	Y
N	86758	86758	86758	86758

Note: Each column reports results from an OLS regression where the dependent variable is ln(Air P ollution) and the key explanatory variable is the standardized subway network density Density$_{it}$/σ. Subway network density in a given location is defined as the weighted sum of subway stations weighted by the squared inverse distance from the location to each subway station in the network. The unit of observation is monitor-day. The weather controls include dummies for daily rain, snow, storm, fog. All columns have controlled for weather, wind directions, and a set of time fixed effects (Year, Season, Day of Week and holidays). Parentheses contain standard errors clustered at the day level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

Table A17: Marginal impact of subway expansion on air pollution

Opening date	Cumulative Standardized Density		Marginal Increase in Density		Marginal Reduction in air pollution (%)	
	non-weighted (1)	ridership-weighted (2)	non-weighted (3)	ridership-weighted (4)	non-weighted (5)	ridership-weighted (6)
Before 2008	0.230	0.201	-	-	-	-
July 19, 2008	0.307	0.300	0.077	0.098	0.154	0.236
Sep 28, 2009	0.365	0.366	0.057	0.066	0.115	0.157
Dec 30, 2010	0.432	0.380	0.068	0.015	0.135	0.035
Dec 31, 2011	0.459	0.391	0.027	0.010	0.054	0.025
Dec 30, 2012	0.577	0.515	0.118	0.125	0.237	0.299
May 5, 2013	0.595	0.532	0.017	0.016	0.035	0.039
Dec 28, 2013	0.604	0.535	0.010	0.004	0.020	0.009
Dec 28, 2014	0.697	0.575	0.093	0.040	0.185	0.095
Dec 26, 2015	0.726	0.587	0.029	0.012	0.058	0.029
Dec 31, 2016	0.735	0.589	0.009	0.002	0.018	0.005
Total			0.505	0.387	1.009	0.930

Note: Network density centered at a TAZ is defined as the weighted sum of subway weighted by the squared inverse distance from the centroid of the TAZ to each subway station operating in the network as of the opening date. It is standardized by dividing its standard deviation. The ridership-weighted density is the reweight of the density by ridership of subway line. Standard deviations of the both densities are $\sigma = 16.38$ and $\sigma = 19.62$ respectively. All density measures are averaged over TAZs for each opening date.

Table A18: Difference-in-difference estimates with a fixed time window

	Dependent variable: ln					
	Without Monitor FE			DID		
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated_{it} \times \mathbf{1}(Post_{it})$	-0.105***	-0.105***	-0.105***	-0.105***	-0.105***	-0.105***
	(0.026)	(0.020)	(0.013)	(0.019)	(0.019)	(0.018)
Temperature (℃)		-0.011***	-0.010***	-0.010***	-0.010***	-0.012***
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Relative humidity (%)		0.008***	0.015***	0.015***	0.015***	0.015***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation (mm)		-0.007*	-0.006*	-0.006*	-0.007*	-0.006
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wind speed (m/s)		-0.078*	-0.205***	-0.104***	-0.106***	-0.103***
		(0.042)	(0.034)	(0.034)	(0.034)	(0.034)
Constant	4.434***	4.144***	3.727***	3.846***	3.854***	3.765***
	(0.018)	(0.104)	(0.140)	(0.141)	(0.153)	(0.153)
Time Window (days)	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$
Weather Controls	N	Y	Y	Y	Y	Y
Wind Directions	N	Y	Y	Y	Y	Y
Wind Directions × Speed	N	Y	Y	Y	Y	Y
Year FE	N	N	Y	Y	Y	Y
Season FE	N	N	Y	Y	Y	Y
Day of Week FE	N	N	Y	Y	Y	Y
Monitor FE	N	N	N	Y	Y	Y
Monitor FE × Driving	N	N	N	N	Y	Y
Monitor FE × Trend	N	N	N	N	N	Y
N	18214	17231	17231	17231	17232	17233
R^2	0.00	0.29	0.45	0.52	0.53	0.54

Note: Each column reports results from an OLS regression where the dependent variable is ln(Air P ollution) and the key explanatory variable the interaction of treatment and post-opening. Columns (4) to (6) show the DID estimates with different sets of controls. The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is monitor-day. The weather controls include dummies for rain, snow, storm, fog. Parentheses contain standard errors clustered at the day level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

Table A19: Difference-in-difference estimates with varying time windows

Dependent variable: ln AQI

	(1)	(2)	(3)	(4)	(5)	(6)
$Treated_{it} \times \mathbf{1}(Post_t)$	−0.046	−0.031	−0.029	−0.052***	−0.057***	−0.052***
	(0.038)	(0.025)	(0.020)	(0.018)	(0.016)	(0.015)
Time Window (days)	τ ±10	τ ±20	τ ±30	τ ±40	τ ±50	τ ±60
	(7)	(8)	(9)	(10)	(11)	(12)
	−0.066***	−0.062***	−0.075***	−0.047***	−0.022	−0.015
	(0.014)	(0.013)	(0.013)	(0.016)	(0.016)	(0.016)
Time Window (days)	τ ±70	τ ±80	τ ±90	τ ±100	τ ±110	τ ±120
	(13)	(14)	(15)	(16)	(17)	(18)
	−0.008	−0.007	−0.009	−0.009	−0.019	−0.023
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Time Window (days)	τ ±130	τ ±140	τ ±150	τ ±160	τ ±170	τ ±180

Note: Each column reports results from an OLS regression using different time windows ((1) to (18): $Open_t$ = τ ±10, τ ±20, . . ., τ ±60, . . ., τ ±180-day) where the dependent variable is ln(Air P ollution) and the key explanatory variable is the treatment indicator (the interaction of the time window dummy and the treated group indicator), T $reated_{it}$ = **1**(P ost_t) × **1**($Distance_{ij}$ ≤ 2km). The May 5th, 2013 opening is dropped from the sample to avoid overlapping events and to extend the time window. The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is monitor-day. All columns control for the daily weather variables: temperature (C_0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed , dummies for rain, snow, storm, fog; the time fixed effects: day-of-week, quarter-of-year, year, holiday-of-sample dummies; spatial fixed effects: dummies for air pollution monitoring stations and the interactions with the time trend and driving restriction policy dummies. Parentheses contain standard errors clustered at date level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

Table A20: Difference-in-difference estimates with continuous time measurement

	Dependent Variable: ln AQI			
	(1)	(2)	(3)	(4)
$Treated_{it} \times \mathbf{1}(Post_{it})$	0.075**	0.151***	-0.001	0.110***
	(0.036)	(0.056)	(0.026)	(0.041)
$Treated_{it} \times \mathbf{1}(Post_{it}) \times Days_{it}$	-0.004***	-0.012***	-0.000	-0.006***
	(0.001)	(0.004)	(0.000)	(0.002)
$Treated_{it} \times \mathbf{1}(Post_{it}) \times Days_{it}^2/100$		0.013*		0.005***
		(0.007)		(0.001)
Time Window (days)	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$	$\tau \pm 60$
N	15467	15467	30933	30933
R^2	0.56	0.56	0.47	0.47

Note: Each column reports results from an OLS regression where the dependent variable is ln(Air P ollution). The treatment group is defined as the monitoring stations within 2km of a new subway line while the control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is station-day. All columns control for the daily weather variables: temperature (C_0), relative humidity (%), precipitation (mm), wind speed (km/h), sets of dummies for wind direction and the interactions with the wind speed , dummies for rain, snow, storm, fog; the time fixed effects: day-of-week, quarter-of-year, year, holiday-of-sample dummies; spatial fixed effects: dummies for air pollution monitoring stations and the interactions with the time trend and driving restriction policy dummies. Parentheses contain standard errors clustered at date level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

Table A21: Difference-in-differences estimates with heterogenous effect

	Dependent variable: ln($Air\ Pollution$)			
	(1)	(2)	(3)	(4)
$N_{it} \times Treated_{it} \times \mathbf{1}(Post_t)$	−0.020***	−0.024***	−0.032***	−0.041**
	(0.007)	(0.007)	(0.007)	(0.018)
Temperature (^0C)	0.010***	0.010***	0.012***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Relative humididy (%)	0.015***	0.015***	0.015***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation (mm)	−0.006*	−0.007*	−0.006	−0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Wind speed (m/s)	−0.104***	−0.106***	−0.103***	−0.130***
	(0.034)	(0.034)	(0.034)	(0.038)
Constant	3.815***	3.826***	3.738***	3.258***
	(0.140)	(0.152)	(0.152)	(0.271)
Time Window (days)	τ±60	τ±60	τ±60	τ±60
Weather Controls	Y	Y	Y	Y
Wind Directions	Y	Y	Y	Y
Wind Directions × Speed	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Season FE	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y
Monitor FE	Y	Y	Y	Y
Monitor FE × Driving	N	Y	Y	Y
Monitor FE × Trend	N	N	Y	Y
Staggered Rollout	N	N	N	Y
N	17231	17231	17231	3314
R^2	0.52	0.53	0.54	0.55

Note: Each column reports results from an OLS regression where the dependent variable is ln(Air P ollution) and the key explanatory variable is the interaction of treatment, post-opening, and number of new subway stations within 2km of each monitor. The control group is defined as the monitoring stations more than 20km away from the new subway line. The unit of observation is station-day. Column (4) relies on the staggered rollout. The weather controls include dummies for rain, snow, storm, fog. Parentheses contain standard errors clustered at date level. Significance: *p < 0.1, **p < 0.05, and ***p < 0.01.

Table A22: Estimates of travel mode choice

(1)		(2)	(3)	(4)
Panel A: Mode Choice Estimation MLE)				
Time (hours)	-0.728***	-0.135***	-0.133***	-0.139***
Cost/Income	0.227***	-0.196***	-0.271***	-0.243***
Case variables				
ASC	Y	Y	Y	Y
Distance	N	Y	Y	Y
Age	N	N	Y	Y
Male	N	N	Y	Y
Schooling	N	N	Y	Y
HH size	N	N	N	Y
# of cars	N	N	N	Y
# of workers	N	N	N	Y
N of Trips	12105	12105	12105	12105
Pseudo R_2	0.059	0.141	0.180	0.199
log ℓ	-15352.1	-14014.5	-13375.2	-13075.5
Panel B: Implied VOT				
Income (RMB/year)	Wage (RMB/h)	VOT (RMB/h)	Wage ($/h)	VOT ($/h)
25000	12.50	7.12	1.98	1.13
75000	37.50	21.38	5.93	3.38
125000	62.50	35.62	9.89	5.64
175000	87.50	49.88	13.84	7.89
225000	112.50	64.12	17.80	10.15
275000	137.50	78.38	21.76	12.40
325000	162.50	92.62	25.71	14.66
Average	37.05	21.12	5.86	3.34

Note: Table reports estimates from maximum likelihood estimation of multinomial logit model of mode choice between driving, walking, biking, subway and bus. Panel A reports coefficients and specifications, where alternative-specific constants are included but not reported. Panel B reports the implied distribution of wages, value of time (VOT) in RMB and USD. Sample is restricted to work-home or home-work trips, at least one car and one bike, age between 16 and 60, within the 6th Ring Road. The value of time (VOT) is calculated as: $VOT = \frac{\frac{\partial v_i}{\partial time_i}}{\frac{\partial v_i}{\partial cost_i}} = \frac{\hat{\gamma}_{time}}{\hat{\gamma}_{cost}} \cdot Income_i = 0.57 \cdot Income_i$. The omitted fixed effect in the model estimated is for walking.

Table A23: Estimates from location choice model

	(1)		(2)	
Panel A: First Stage Estimates (MLE) - 20 Sampled Alternatives				
	Specification I		Specification II	
Variable	**coef.**	**std. error**	**coef.**	**std. error**
$\frac{\log(\text{housing price})}{\log(\text{HH income})}$	-0.974	0.0093	-1.17	0.0085
age buyer*unit size	0.0009	0.00007	0.0009	0.00007
(age buyer)^2*unit size	$-7.2*10^{-6}$	$1.5*10^{-7}$	$-6.5*10^{-6}$	$1.5*10^{-7}$
mode choice log sum	0.0037	0.0007		
Households	13,865		13,865	
Housing Types	548		548	
Log-Likelihood	-495,483		-496,885	
LR p-val (H0: $\delta = 0$)	0.00		0.00	
McFadden pseudo-R^2	0.54		0.51	

	(1)		(2)		(3)	
Panel B: Second Stage Estimates: Dependent variable is $\hat{\delta}_{jt}$						
	OLS		**OLS**		**IV**	
variable	**coef.**	**S.E.**	**coef.**	**S.E.**	**coef.**	**S.E.**
log(total price)	-0.470	0.24	-0.271	0.233	-1.736	0.773
Dist. to center	-0.0125	0.00925	-0.0225	0.00927	-0.0522	0.0268
unit size in m^2	0.149	0.0158	0.128	0.015	0.138	0.0192
(unit size)^2	-0.00070	$8.74*10^{-05}$	-0.00061	$8.23*10^{-05}$	-0.00060	$8.52*10^{-05}$
constant	-0.399	3.255	-1.954	3.176	17.34	13.37
Observations	548		548		548	
R^2	0.22		0.36		0.31	
Year FE	X		X		X	
District x Ring Road FE			X		X	
1st Stage F-Stat					11.9	

Note: Table reports estimates from a two-stage estimate of demand for housing. The first stage estimates are presented in Panel A, where "mode choice logsum" is EVj constructed using data for households and estimates from the mode choice model from Table 4.2. First stage housing type fixed effects are estimated through the contraction mapping in this first stage and are used as the dependent variable in the second stage reported in Panel B. Panel B estimates are based on housing type attributes and are estimated by OLS and IV, where the instruments are the mean of housing attributes other than price within 1-5km rings from the housing types.

Table A24: Simulation results: commuting mode only

	(1) Baseline No Policy *(in levels)*		(2) Driving Restriction *(change rel. to I)*		(3) Congestion Charge *(change rel. to I)*		(4) Subway Expansion *(change rel. to I)*	
Household Income Relative to Median								
Below		**Above**	**Below**	**Above**	**Below**	**Above**	**Below**	**Above**
Mode Use Share in Percentage Points								
Drive	0.07	0.38	-0.01	-0.08	-0.02	-0.01	-0.01	-0.02
Subway	0.03	0.12	0.00	0.03	0.00	0.01	0.02	0.07
Bus	0.32	0.15	0.01	0.04	0.01	0.00	0.00	-0.02
Bike	0.17	0.10	0.00	0.00	0.01	0.00	-0.01	-0.01
Walk	0.41	0.25	0.00	0.01	0.00	0.00	0.00	-0.02
Speed (kph)	57.8	57.6	2.3	2.4	1.6	1.8	0.9	0.8

Note: Table reports results from three counterfactual policy simulations based on 2014 observations relative to simulated baseline no-policy equilibrium with 2008 subway network (column I): driving restriction, 20 RMB congestion charge and expanding the subway from 2008 to 2014 network. “Change in Mode Use Share” reports how the share of commuters in each income quartile changed their commuting choice (0.03 means that the share using that mode increased by 3 basis points)

Table A25: Simulation results: commuting & location choice

	(1) Baseline No Policy *(in levels)*		(2) Driving Restriction *(change rel. to I)*		(3) Congestion Charge *(change rel. to I)*		(4) Subway Expansion *(change rel. to I)*	
Household Income Relative to Median								
Below		**Above**	**Below**	**Above**	**Below**	**Above**	**Below**	**Above**
Mode Use Share in Percentage Points								
Drive	0.08	0.37	-0.04	-0.15	-0.04	-0.07	-0.01	-0.07
Subway	0.03	0.11	0.02	0.07	0.01	0.05	0.02	0.12
Bus	0.32	0.15	0.02	0.03	0.01	0.02	-0.01	-0.02
Bike	0.17	0.11	0.01	0.01	0.02	0.00	0.00	-0.01
Walk	0.40	0.26	0.01	0.02	0.00	0.00	0.00	-0.02
Dist. to Subway in KM	1.89	4.21	0.08	-0.03	-0.03	0.10	0.08	-1.11
Dist. to Work in KM	10.1	9.40	1.94	-1.01	-2.9	2.5	1.09	-2.0
Speed in KPH	57.8	57.6	3.5	3.5	2.8	2.9	1.8	1.7

Note: Table reports results from three counterfactual policy simulations based on 2014 observations relative to simulated baseline no-policy equilibrium with 2008 subway network (column I): driving restriction, 20 RMB congestion charge and expanding the subway from 2008 to 2014 network. “Change in Mode Use Share” reports how the share of commuters in each income quartile changed their commuting choice (0.03 means that the share using that mode increased by 3 basis points.

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